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Full Length Research Paper

A comparative study on prediction of sediment yield in the Euphrates basin

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Agricultural fields' fertility decays and dam reservoirs are filled due to sediment movement. Sediment amount which is carried by a river depends on the river's flow rate, inclination of its base and time. In this study, sediment estimations of Euphrates basin which was selected as the area for practice, is the largest basin in Turkey and contains its largest dams, based on classical formulations like Du Boys, Meyer-Peter-Müller, Schoklitsch, Shields and Garde-Albertson. Then, sediment values were estimated by using artificial neural networks (ANN) having a network architecture, which was developed by the authors. High correlation was observed between the values found by using a feed-forward and back-propagation and the observed values of ANN. This evidence, emphasizes how effective and efficient this method is, compared with classical methods. Design of reservoirs dead storages depends on realistic and reliable estimation of sediment yield. In this study, more realistic values have been obtained with ANN model compared with classical equations. Moreover, when sediment measurement cannot be conducted for a certain period, its amounts for the absent period may be estimated by using ANN technique with a little error.

Key words: Sediment yield, back propogation, artificial neural network, Euphrates basin.

INTRODUCTION

Sediment amount carried by a river is a basic datum in solving engineering problems about that river. Sediment yield should be determined especially in selecting water storage field and type, structures of waterpower, determining capacity of the dam reservoir, arrangements like transportation and flood control and determining possible accumulations and carving, which may occur while crossing the river by bridges. In brief, there is no doubt that sediments affect existing structures or structures to be constructed from the point of view of function, robustness and cost as well as aesthetics (Erkek and Ağıralioğlu, 2002; Yenigun and Erkek, 2007). Rivers' flow and sediment should be observed and correlation between observation results and the basin's characteristics should be determined for well planning studies on soil and water resources development (Yenigun et al., 2008). In this chain of events beginning with erosion and ending with sediment, it is very hard to consider the events of erosion, sediment and its movement separately. Although, it is very interesting that these events are ultimately serious problems causing losses in water and soil assets as well as agricultural pollution, studies are very limited in Turkey. Carried sediments reduce fertility of agricultural fields and fill dams' reservoirs. Percentage of these grains should not exceed certain limits in waters used in industry and also daily life, because they increase turbidity of water and decrease its quality (Baylar et al., 1999). According to

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Firat and Güngör (2004), carried coarse grains may abrade legs of bridges, connection surfaces and coated channels. Big rocks carried along highly inclined rivers may cause damages on structures to be constructed on surface of the rivers. Sediment movement through dams' reservoirs cannot be prevented completely. Sediment yield, which is carried by a river, depends on the river's discharge, inclination of its base and time. Some of the literature study on sediment movement is summarized below;

Luk et al. (1997) worked in Shenchong experimental basin which is located in subtropical Deqing County, in the hilly region of South China. Yin et al. (2000) assessed water movement in five harbour-models to determine the local solute-concentrations under both tidal and steady flows. A three-dimensional baroclinic model, including suspended sediment transport, is used in cross-sectional form to examine the processes (tidal, along-shelf current, wind-waves and wind) influencing suspended sediment transport off the west coast of Scotland (Davies and Xing, 2002). In another research, the sediment yield of the Upper Yangtze River (Yichan) showed no visible trend in change, while its two largest tributaries showed different variations in sediment yield; with a decrease in Jialing River and an increase in the Jinsha River during the period of 1950s to the 1990s (Zhang and Wen, 2004).

To test the generality of insight obtained from recent STRATAFORM, a comprehensive program for sediment transport and accumulation studies of Northern California's Eel margin, river sediment sources and continental shelf sinks were examined on the Pacific Northwest margin from 38° to 44.5° N by Wheatcroft and Sommerfield (2005). Tamene et al. (2006) used the reservoir sedimentation and corresponding catchment attribute data for investigating the major factors controlling sediment yield variability in a mountainous dryland region of northern Ethiopia. Vericat and Batalla (2006) reported that the sediment transport of the highly regulated lower Ebro River is estimated on the basis of a measuring programme carried out between 2002 and 2004. Restrepo et al. (2006) studied the Magdalena River which has the highest sediment yield of any medium sized or large river in South America. Kasai et al. (2005) explained that forest clearance modified the pattern and rate of sediment delivery to valley floors via shallow landslides and gully complexes in a steep headwater catchment in New Zealand.

Some models were developed by using environmental factors to characterise a drainage basin in terms of sensitivity to erosion and sediment transport by Vente and Poesen (2005). A tank model consisting of three tanks was developed for prediction of runoff and sediment yield in Northwestern Mississippi by Lee and Singh (2005). Öztürk et al. (2003). In their study, runoff depth and sediment quantities were predicted using Agricultural Non-Point Source pollution model (AGNPS) in Bilecik, Turkey. In Turkey, sedimentation which is the natural result of erosion occurring by different factors, is known to have an adverse effect on the development of soil and water resources. In the study of Fırat and Gungor (2004), the suspended sediment amount carried by stream is determined by the feed forward neural network method. In this study, the training sets for the problem were generated through sediment measurements which have been performed by General Directorate of Electrical Power Resources Survey and Development Administration of Turkey. The vector method applied was used to calculate sediment transport patterns, giving an idea of sediment transport directions together with the main areas of deposition and the possible dispersal patterns of contaminants in the Izmir Bay environment (Duman et al., 2004). Neural network approaches have been successfully applied in a number of diverse fields, including water resources (Kisi, 2005). In the hydrological forecasting context, recent experiments have reported that artificial neural networks (ANNs) may offer a promising alternative for streamflow prediction (Raman and Sunilkumar, 1995; Zealand et al., 1999; Chibanga et al., 2003; Cigizoglu, 2003; Kisi, 2004; Cigizoglu and Kisi, 2005), reservoir inflow forecasting (Saad et al., 1996; Jain et al., 1999), suspended sediment estimation (Kisi, 2005) and rainfall–runoff modelling (Sudheer et al., 2002; Wilby et al., 2003; Solomatine and Dulal, 2003). Some of the studies evaluating sediment movement with ANN are mentioned below.

In the study of Cigizoglu (2002a), the sediment concentration estimation, using only observed river flow values and the previous sediment value in a nearby river as input, provided realistic approximations in terms of mean squared error and total sediment amount. The ANN estimates are compared also with corresponding classical regression ones. In another study of Cigizoglu (2002b), a comparison is made between ANNs and sediment rating curves for two rivers with very similar catchment areas and characteristics in the North of England. Data from one river are used to estimate sediment concentrations and flux in the other for both estimation techniques. The majority of the artificial neural network applications in water resources involve the employment of feed forward back propagation method. In Cigizoglu and Alp (2005)'s study, generalized regression neural network was used in river suspended sediment estimation. The neural networks are trained using daily river flow and suspended sediment data belonging to Juniata catchment in USA. They observed that the neural network estimations are found significantly superior to conventional method results. The study about Tigris River is aimed to establish mathematical models between suspended-sediment and various combinations of rainfall, temperature and water discharge through ANNs and Regression Analysis (Kayaalp and Hamidi, 2004). Doğan (2009) study, was to establish an effective model which includes nonlinear relations between dependent

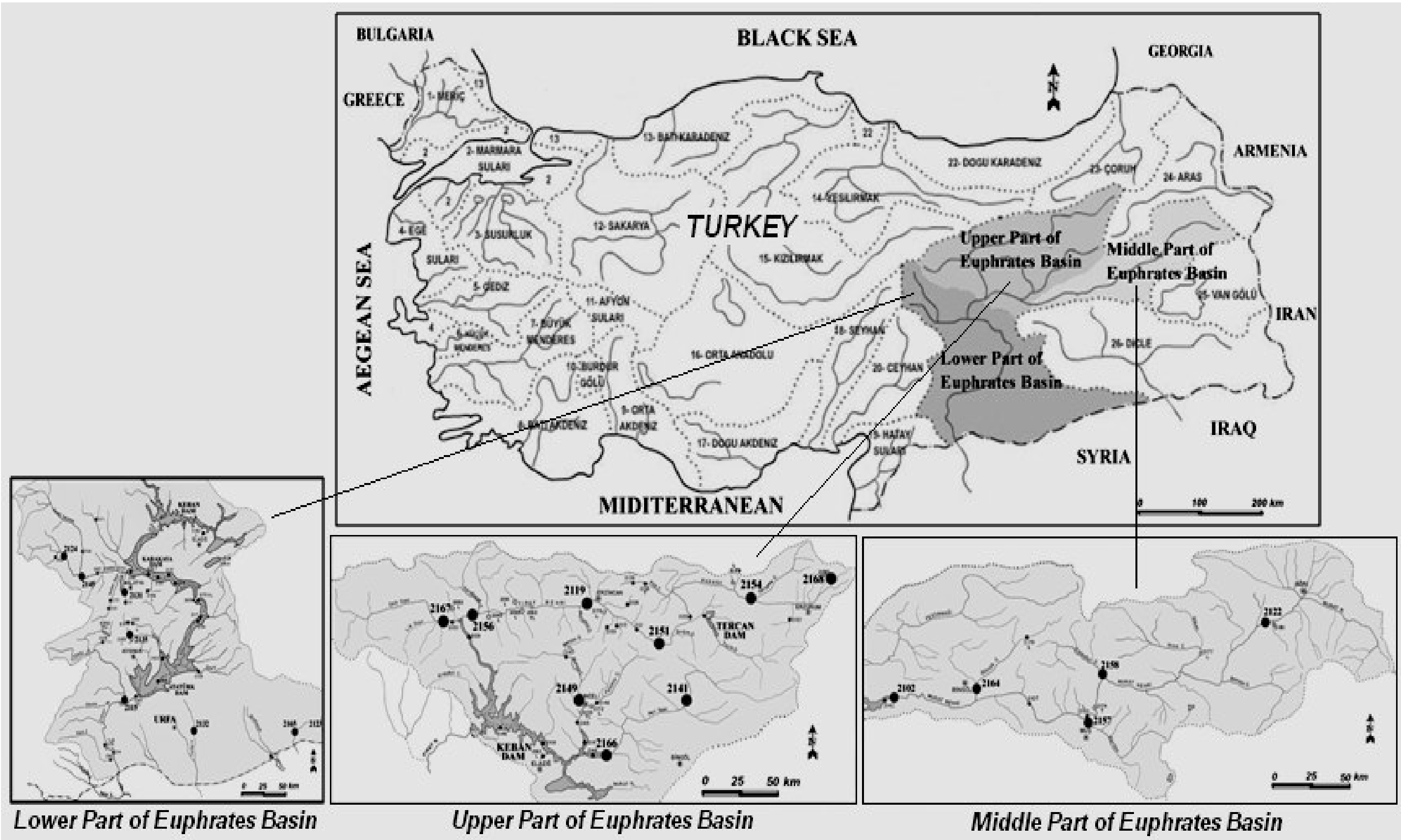

Figure 1. Study area.

(suspended sediment concentration) and independent (bed slope, flow discharge and sediment particle size) variables. The results of that study shows that ANN model is found to be significantly superior to others. In another study, soil loss and sediment yield estimation model was developed. Parameters such as erosive rainfall, land use, surface cover, slope and sediment delivery ratio were used in that model. (İrvem, 2003).

The artificial neural network (ANN) has been successfully used in the hydrological sciences during recent years (Cigizoglu and Kisi, 2005). The recent experiments indicated that the ANN (Bilhan et al., 2010) that addresses the application of the neural network and some classical formulas together like Du Boys, Meyer-Peter-Müller, Schoklitsch, Shields and Garde-Albertson for the estimation of sediment yield. This provided an impetus for the present investigation. The main aim of this study is to develop a suitable and more reliable ANN model for predicting the sediment yield instead of classical formulations. Because the Euphrates Basin is the largest and has the largest dams in Turkey, it has been selected for application in this study. The neural network architecture used in this study is significant, because it is compared with classical methods and emphasizes its efficiency in estimating sediment yield.

MATERIALS AND METHODS

Sediment yield of a basin is calculated via equations given in the literature by using the data from selected flow observation and measurement stations among many of those existing in that basin. However, the equations in which the parameters affecting sediment yield of the basin become clear should be used, because the methods for calculating sediment amount given in the literature are theoretical-empiric and the results are altered depending on different parameters. On the other hand, it was aimed to make a new calculation by benefiting from ANN, which is one of the actual and modern methods and finally, to compare all results with the sediment amount calculated based on observation as well as to determine the correlation between them and how strong it is. Thus, it was aimed to develop the most realistic method based on the basin for determining sediment amount through comparison of flow data, observational sediment amounts, classical equation calculations and ANN calculation results.

Study area

In this study, Euphrates Basin was investigated (Figure 1). It exists in Southeastern and Eastern regions of Turkey and it is the main river in the basin. Determining sediment yields carried by Euphrates is highly important because of the dams existing in the basin. Euphrates River rises in Erzurum Mountains and collects water from the mountainous area accounting for upper part of the river basin during its flowing toward southwest. Average annual flow rate of Euphrates River is 31.6×10^9 m^3 (Akçakoca, 1997).

Average annual flow rate of Euphrates River is estimated as 30.377 x 10^6 m^3 for the years between 1937 and 1980 in Belkısköy (Birecik) near the border to Syria. The station has a basin covering 100.702 km^2. Average annual flow rate for 1973 in which the worst drought was experienced is around 62% of the mean. Average annual flow rate was 53.548 x 10^6 m^3 accounting for 186% of the mean in 1969 in which the highest precipitation was taken. Seasonal changes in flow rate of the river are also interesting. Flow rate is highest in April and lowest in September in an ordinary year. Monthly flow rate ranges between 275 and 33% of the annual mean in an ordinary year (GAP-Southeastern Anatolian Project, 2006). Euphrates Basin covering 127304 km^2 with an average height of 1009.87 m is the largest water basin in Turkey. Average precipitation taken by Euphrates Basin is 540.1 mm/year and average annual flow is 31.61 km^3 (EİE, 2000). Euphrates Basin is divided into three; lower, middle and upper Euphrates:

Data

Suspended matters are measured by General Directorate of Electrical Power Resources Survey (EİE) and Development Administration and General Directorate of State Hydraulic Works (DSİ). Key curves are drawn for suspended matters according to the measurement results obtained during observation time. Thesekey curves are drawn by using logarithmic conversions of the values of suspended matter amount (ton/day) and suspended matter concentration (PPM) as well as flow rate (m^3/s) at the moment these samples are taken. Features of the active monitoring stations, which are managed by EİE in Euphrates Basin, are seen in the table. The practice was conducted with five stations, which have statistically sufficient data, of the ones selected and are seen in Table 1. Statistical parameters of the data belonging to these stations were calculated in Table 2.

Methods

Suspended matter amounts and concentrations for the five sediment monitoring stations selected in Euphrates Basin were determined by using the following methods respectively and the obtained results were compared:

- Observational key curves (developed by EİE)
- Classical-theoretical equations
- Artificial neural networks

Sediment observation curves which were found by using the observed sediment amounts in the selected five observation stations were compared with the curves obtained by employing five different classical methods. Then, sediment curves were obtained for the same stations with the help of ANN and were compared with the results obtained previously. Herein, an ANN approach is utilized for the prediction of sediment yield by using the quantity of flow data values. Estimation of sediment yield is achieved through ANN models, which consist of one input, one hidden and one output layers. Then, correlation was evaluated by considering relations among results of conventional equations, ANN models and observed values. Finally, the most suitable formula for sediment calculation of the area under investigation and effective parameters within it were determined and examined.

Classical-theoretical equations for calculating sediment yield

Most of the sediment movement functions allow estimation of the amount of carried sediment under stable hydraulic and bed material conditions. Some transportation equations were designed for finding only bed or suspended matter load, while others allow calculation of the total matter load. This discrimination is important especially in sand-bed rivers. In such type of rivers, suspended matter amount may be many-fold of bed matters' load. Another significant difference between sediment transportation functions is related to matter size. Most of the sediment transportation functions were designed for a single matter size. They are suitable if a balanced transportation is assumed. Equations which were developed for different material sizes should be used in studying movement events under instable circumstances like flood.

There are many equations in literatures for determining matter amount carried by rivers. Some of them may be listed as Du Boys, Meyer-Peter Müller, Schoklitsch, Shields, Einstein-Brown, Einstein bed load function, Laursen, Blench, Colby, Engelund-Hansen, Inglis and Toffeleti. We used the equations of Du Boys, Meyer-Peter Müller, Schoklitsch, Shields and Garde Albertson, which mostly yield effective results, in our study. (Özbek and Özcan, 200; Erkek and Ağıralioğlu, 2002; Yanmaz, 2006; Ünsal, 1978; USBR, 1987; Vanoni, 2006). Du Boys showed that sediment transportation is a result of the difference between hydraulic shearing force and critical shearing force of bed material and the average cross-section can be calculated by using hydraulic parameters. He assumes that drift tension decreases linearly along thickness of the moving layer downward.

$$g_s = \psi_d \tau_0 (\tau - \tau_{kr}) \qquad (1)$$

In this equation, g_s stands for weight of the drifted matter passing through unit width, τ_0 :for drifting tension on river bed, τ_{kr} :for critical drift tension and ψ_d : for the factors depending on diameter of drifted matter. Schoklitsch designed the following equation by assuming that sediments consist of homogeneous grains in diameter (2).

$$g_s = 7000\, d^{1/2} j^{1/2} (q - q_0) \qquad (2)$$

In equation (2), g_s : stands for weight of the drifted matter passing through unit width, d : grain diameter, j: inclination of basin, q : flow rate passing through unit width of bed and q_0 : critical flow rate passing through unit width of bed.
Shields equation is seen below;

$$g_s = \frac{[10 \quad q \quad j \; (\tau_0 - \tau_{kr})]}{\left\{ \left[\frac{\gamma_s}{\gamma} - 1 \right]^2 \right\} d_{50}} \qquad (3)$$

In equation (3), g_s : stands for weight of the drifted matter passing through unit width, q : flow rate passing through unit width, τ_0 : drift tension, τ_{kr} : d_{50} critical drift tension value for the sediment size, j : flow inclination, γ_s : specific weight of drifted sediment, γ : specific weight of water, d_{50} : median size for sediment and d_{si} : average diameter of the portion passing through the sieve (Erkek and Ağıralioğlu, 2002). The equation designed by Meyer - Peter and Müller is seen in Equation 4.

Table 1. Working stations on Euphrates Basin and specifications of selected stations (EİE, 2006).

Station number	Station name	Date of open	Area (Km^2)	Altitude (m)	Geographic coordinates	Selection	Data interval	Number of data
2102	MURAT S.-PALU	26.07.1936	25515.6	859	39 56 22E-38 41 49N	X	1962-2005	474
2103	FIRAT N.-KEBAN	03.08.1936	63873.6	698	38 43 54E-38 48 07N			
2115	Göksu-Malpınar	15.02.1953	3998.8	397	38 09 26E-37 29 36N	X	1977-2005	378
2119	Fırat N.-Kemah Boğazı	04.09.1953	10356.0	1123	39 23 36E-39 41 00N	X	1965-2005	463
2122	Murat-Tutak	09.09.1953	5882.4	1552	42 46 49E-39 32 19N			
2124	Tohma S.-Yazıköy	01.09.1954	1256,1	1180	37 26 33E-38 40 21N			
2131	Bey D.-Kılayık	07.09.1956	277.6	925	38 12 36E-38 19 21N			
2133	Munzur S.-Melekbahce	31.07.1953	3284.8	875	39 31 35E-39 02 39N	X	1962-2005	344
2135	Bulam Ç.-Fatopaşa	28.09.1957	166.4	1240	38 44 49E-37 59 26N			
2145	Tohma Suyu-Hisarcık	30.06.1962	5822.0	935	37 41 08E-38 28 32N	X	1990-2005	193
2149	Munzur S.-Miskisağ	17.01.1963	1669.0	900	39 32 35E-39 06 29N			
2151	Fırat N.-Demirkapı E.E.Y.	13.06.1963	8185.6	1355	40 10 05E-39 34 41N			
2154	Karasu-aşağı kağeariç	01.10.1968	2886.0	1675	40 45 33E-39 56 16N			
2156	Fırat N.-Bağıştaş	01.10.1968	15562.0	865	38 26 55E-39 25 57N			
2157	Karasu-Karaköprü	15.11.1968	2098.4	1250	41 29 43E-38 47 02N			
2158	Bingöl Ç.-Abdurahm. K.	19.11.1968	1577.6	1310	41 29 14E-39 06 30N			
2162	Fırat N.-Eriç	09.07.2003		995	38 57 08E-39 35 06N			
2164	Göynük Ç.-Çayağzı	07.11.1968	2232.0	998	40 33 32E-38 48 06N			
2166	Peri S.-Loğmar	01.11.1968	5385.8	847	39 48 50E-38 51 31N			
2172	Pülümür Ç.-Batman KÖP.	14.11.1977	1374.0	890	39 33 55E-39 06 20N			
2174	Murat N.-Akkonak	01.10.1979	17435.1	1285	41 31 11E-39 02 29N			
2176	Tacik D.-Mutuboğazı	01.03.1983	94.4	1225	39 52 19E-39 35 24N			
2177	Hınıs Ç.-Adıvar	28.05.1985	2995.3	1452	42 10 06E-39 13 10N			
2179	Kop Suyu-Pırnakapan	04.10.1996	9.0	1780	40 33 44E-39 59 15N			
2180	Dumlu Ç.-Yeşildere	03.06.1997	52.3	1935	41 24 31E-40 08 19N			
2181	Arabalı D.-Tutak	17.06.1997	117.3	1615	42 49 35E-39 31 31N			
2183	Pamukçayı - Kocali	18.12.1998	68.0	1028	38 16 46E-37 56 06N			

Table 2. Statistical parameters of studied stations' data.

Stations	Variables	x_{mean}	S_x	C_v	C_{sx}	x_{max}	x_{min}	X_{max}/X_{mean}
2102	Flow (m^3/sec)	254.05	354.12	1.39	2.63	2.289.28	14.33	159.75
Murat S.-Palu	Sediment (t/day)	38.020.10	109.451.50	2.88	5.35	1.121.616.60	45.80	24.489.45
2115	Flow (m^3/sec)	52.05	50.32	0.97	2.53	348.70	6.16	56.61
Göksu-Malpınar	Sediment (t/day)	5.750.10	18.305.60	3.18	5.70	162.177.30	21.29	7.617.53
2119	Flow (m^3/sec)	91.59	94.47	1.03	1.99	523.87	13.35	39.24
Fırat N.-Kemah B	Sediment (t/day)	6.198.03	17.467.10	2.82	4.40	134.433.50	35.38	3.799.70
2133	Flow (m^3/sec)	85.84	75.67	0.88	1.90	417.78	22.19	18.83
Munzur S-M.Bahçe	Sediment (t/day)	4.056.30	12.021.30	2.96	6.50	141.046.40	6.30	22.388.32
2145	Flow (m^3/sec)	19.79	12.15	0.61	4.14	116.41	8.82	13.20
Tohma S-Hisarcık	Sediment (t/day)	1.044.00	3.352.99	3.21	5.92	26.215.30	32.35	810.37

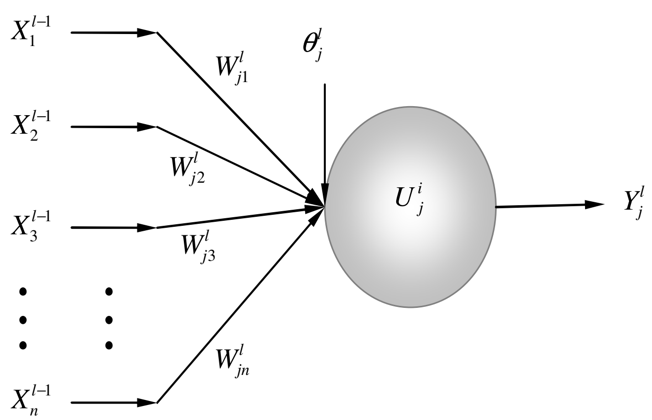

Figure 2. Simplified model of an artificial neuron.

$$q_s = \left(\frac{k_s}{k_\gamma}\right)^{3/2} \gamma R^{2/3} j = [0.047(\gamma_s - \gamma)\, d_m] + \left\{0.25\left(\frac{\gamma}{9}\right)^{1/3}\left[\frac{(\gamma_s - \gamma)}{\gamma_s}\right] g_s^{2/3}\right\} \quad (4)$$

In equation (4), g_s : stands for weight of the drifted matter passing through unit width, j : friction inclination, k_s : Stricler porosity coefficient, $k_r = \dfrac{26}{(d_{90})^{1/6}}$: grain porosity coefficient, R : hydraulic radius , d_m :effective grain diameter: $\sum (P_i\, d_{si})$, P_i : % amount passing through the sieve (Özbek and Özcan, 2001). The following equation was designed by Garde Albertson:

$$q_t = 16\ \tau_*^{\ 4}\ \gamma_s\ u_*\ d \quad (5)$$

The relation between τ* and u* is given as the following:

$$\tau_* = \frac{\tau_0}{(\gamma_s - \gamma_f)\, d} \quad (6)$$

$$\tau_0 = \gamma\, R\, j \quad (7)$$

$$u_* = \sqrt{g\ \ j\ h} \quad (8)$$

Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are massively parallel systems composed of many processing elements connected by links of variable weights. The backpropagation network is by far the most popular among the many ANN models (Bilgehan and Turgut, 2010; Bilgehan, 2010; Lippman, 1987; Kisi, 2008). These networks are similar to the biological neural networks in the sense that functions are performed collectively and parallel with the units; rather than having a clear description of sub-tasks to which various units are assigned. The term artificial neural network currently tends to refer mostly to neural network models employed in statistics and artificial intelligence. ANN models are designed with emulation of the central nervous system in mind; which makes them also subjects of theoretical neuroscience (Tapkin, 2004; Tapkin et al., 2006).

The neural network is created for two different phases in the most general sense. The first is the training phase and the second is the testing (simulation) phase (Tapkin et al., 2006). ANNs have the ability of performing with a good amount of generalization from the patterns on which they are trained. Training consists of exposing the neural network to a set of known input - output patterns (Kartam et al., 1997; Rafiq et al., 2001; MathWorks Inc. 1999; Ashour and Alqedra, 2005). Several methods do exist to train a network. One of the most successful and widely used training algorithms for multi-layered perceptron (MLP), is the backpropagation (Kartam et al., 1997; Flood and Kartam, 1994). The neural network is operated using backpropagation training algorithm in this study. Backpropagation neural networks generally have a layered structure with an input, output and one or more hidden layers (Kewalramani and Gupta, 2006). Simplified model of an artificial neuron can be seen in Figure 2. The modification process is continued in the output layer, where the error between

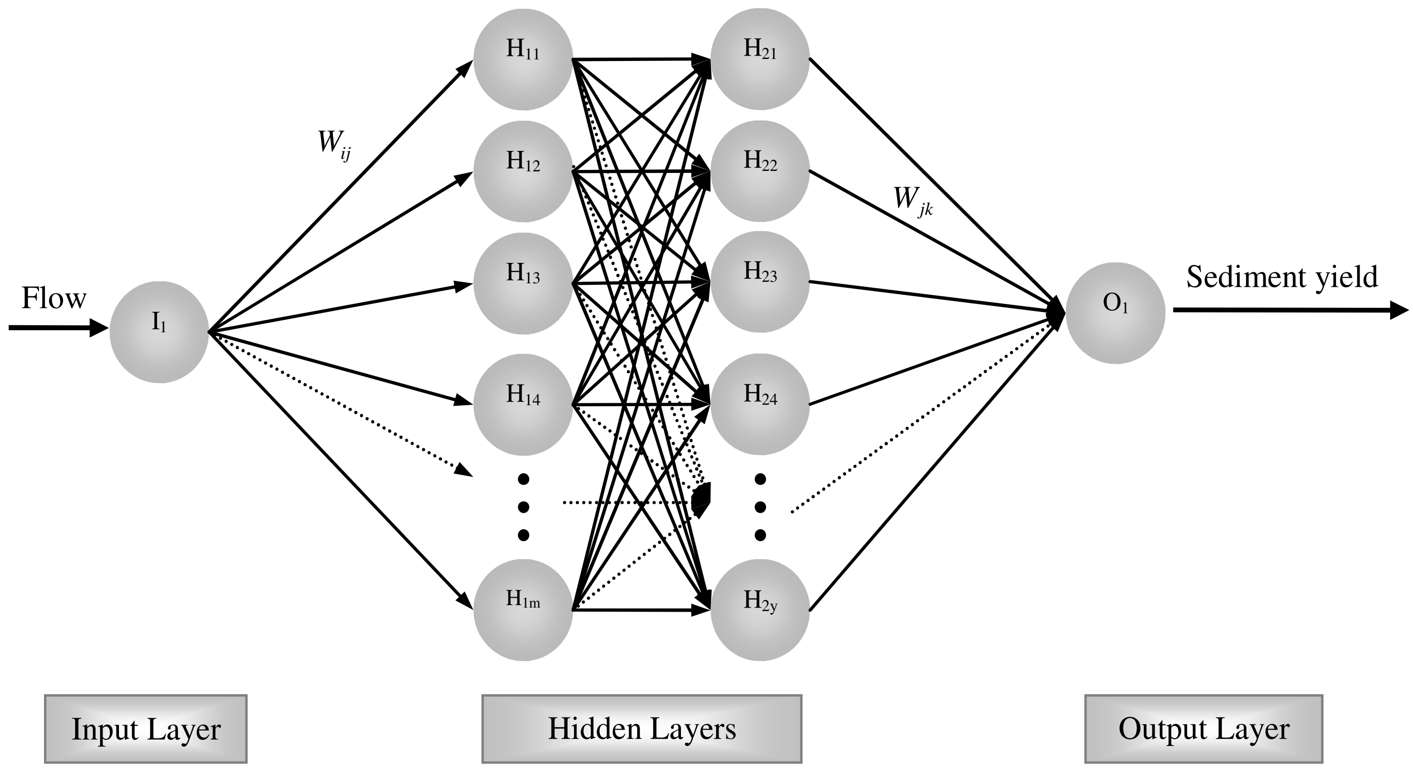

Figure 3. The used Artificial Neural Network topology.

the network outputs and desired targets is calculated and then propagated back to the network through a learning mechanism. The generalized delta rule is a widely used learning mechanism in backpropagation neural networks (Rajagopalan, 1973). The implementation of such algorithm updates the network weights in the direction; in which the performance function decreases most rapidly (reduces the total network error in the direction of the steepest descent of error) (Kewalramani and Gupta, 2006). The network consists of layers of parallel processing neuron elements with each being fully connected to the proceeding one by interconnection strengths or weights, W (Kisi, 2005). Figure 3 illustrates the used topology of three-layer neural network consisting of input, hidden and output layers. Any difference between the output values expected from the input pattern is interpreted as an error in the system. Weights of the networks are then used to adjust the using error backpropagation and gradient descent techniques aiming to minimize the error. The weight update is calculated from the partial derivative of the error function multiplied by a constant, known as the learning rate. The input training patterns are propagated forward through the network; the mean squared error is summed and the error is then back propagated through each layer until the input layer is reached to calculate the abovementioned last term (Todd and Challis, 1999). The training performance goal is the best yield which can be reached. The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm can then oscillate and become unstable. If the learning rate is too small, however, the algorithm then takes too long to converge. The gradient is computed by summing its calculations at each training example and the weights are only updated after all training examples, termed as epoch, have been presented (MathWorks Inc., 1999). The ANN model is tested and the results compared by means of correlation coefficient (R^2), root mean square errors (RMSE) and mean absolute errors (MAE). The statistical formulations of these parameters are given below:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(C_{i,observed} - C_{i,estimated}\right)^2}{\sum_{i=1}^{N}\left(C_{i,observed} - \tilde{C}_{i,observed}\right)^2} \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_{i,observed} - C_{i,estimated}\right)^2} \tag{10}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|C_{i,observed} - C_{i,estimated}\right| \tag{11}$$

Where $C_{i,estimated}$, $C_{i,observed}$ and $\tilde{C}_{i,observed}$ are the estimated, observed and average of observed output of the network, respectively and N is the total number of training patterns.

APPLICATIONS AND RESULTS

In this article, sediment estimations were conducted by

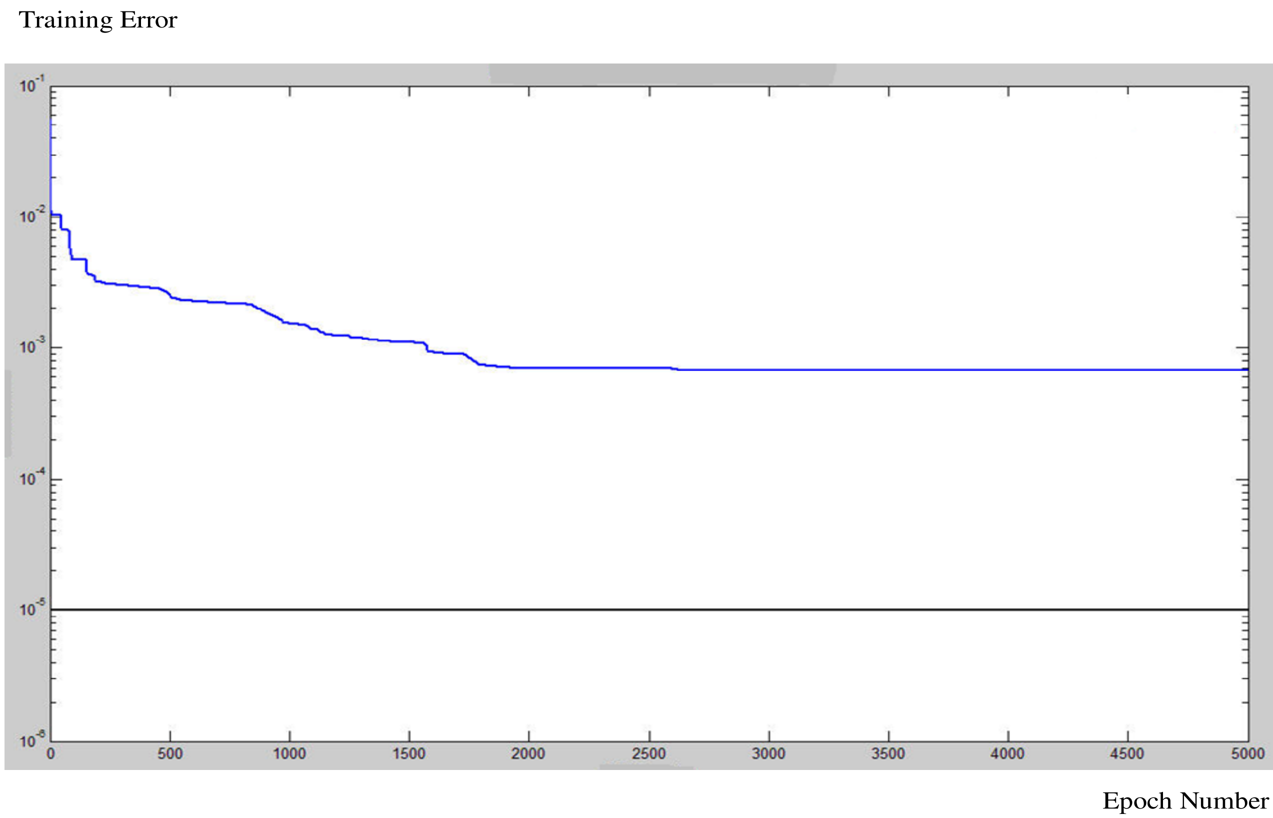

Figure 4. The training error graph for the neural network model; Training error versus Epoch number.

using the long-term (between the years of 1962 - 2005) and large data (Total data number = 1852) provided by five stations on Euphrates Basin selected for investigation and equations of Du Boys, Meyer-Peter Müller, Schoklitsch, Shields and Garde Albertson generally yielding reliable results as well as ANN model. R^2 values were entered into the graphics on which estimations were shown along with the observed values as the correlation. Then, the typical multi-layer feedforward neural networks are used in the current application. The problem in this study can be defined as a nonlinear input-output relation among the influencing factors for neural network analyses. The backpropagation algorithm and construction of the neural network model were carried out in the conceptual ANN simulation. There was one node in the input layer corresponding to quantity of flow and one node in the output layer corresponding to sediment yield. All of the data was divided into two sets; one for the network learning named training set and the other for testing the network named testing set. Each of the training and testing set cover about 50% of the total data. The data set is normalised before the analyses and the predictive capabilities of the feedforward back-propagation neural network are examined. The normalization of the data was carried out using Equation (12) which restricts the data range within an interval of 0 - 1.

$$C_i^{\text{norm}} = \frac{C_i - C^{\min}}{C^{\max} - C^{\min}} \tag{12}$$

Where C_i^{norm} and C_i are the normalized and unnormalized values of the data set, respectively, $C^{\max}$ and $C^{\min}$ are the maximum and minimum values of the data set under normalization, respectively.

The methodology used here for adjusting the weights is called momentum backpropagation; based on the generalized delta rule presented by Rumelhart et al. (1986). The learning rates were used for increasing the convergence velocity throughout all ANN simulations. The sigmoid function and linear function were additionally used for the activation functions of the hidden and output nodes, respectively. The hidden layer node numbers of each model were determined after trying various network structures, since no theory yet exists clarifying the number of hidden units needed to approximate a given function. The training of the networks was stopped after 5,000 epochs; when the variation of error became sufficiently small. The error graph for an ANN model during training is shown in Figure 4. It can be seen in the

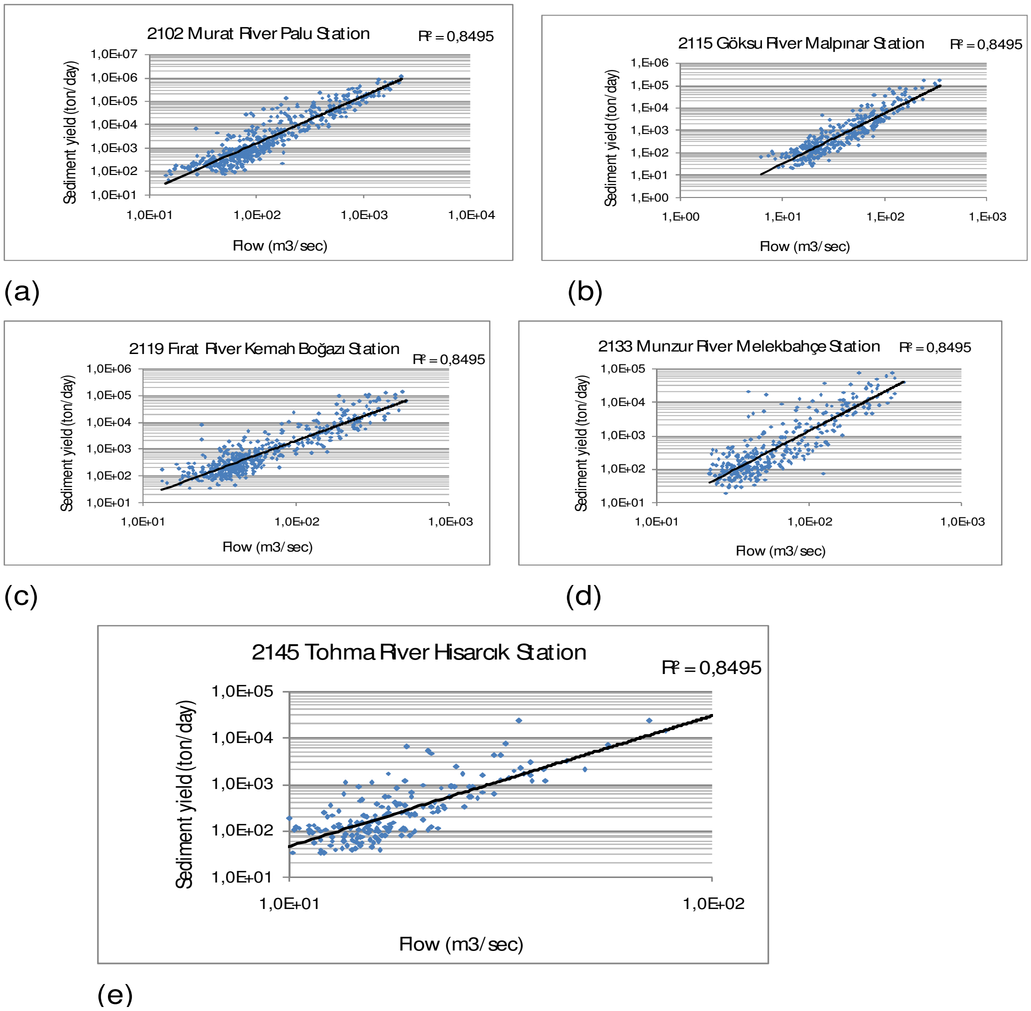

Figure 5. Relationship for flow (m^3/sec) and observed sediment yield (ton/day) for stations studied. (a) 2102 Murat River Palu, (b) 2115 Göksu River Malpınar. (c) 2119 Fırat River Kemah Boğazı, (d) 2133 Munzur River Melekbahçe. (e) 2145 Tohma River Hisarcık.

figure, that the necessary epochs to reach the training goal was approximately 5,000. This shows that the training of the network was carried out on a sensitive manner enabling the determination of mean squared error on a dependable basis. In other words, this high epoch number signified the acuteness in the carried calculations. The computer program code for the ANN simulation was written in MATLAB language. Different hidden neuron number were tried using this code and then the appropriate model structure was determined for data sets. Numerous trials were carried out in the neural network environment to determine neuron number of the hidden layers. Optimum hidden neuron numbers were obtained for different cases. The ANN model was then tested and the results were compared by R^2, RMSE and MAE.

The network parameters number of; input layer neurons was one, hidden layer neurons was nine for stations of 2102, 2115 and 2119, and eleven for stations of 2133 and 2145. Number of hidden layers was one and number of output layer neurons was also one. Moreoever, the type of backpropagation learning rule was gradient descent algorithm, activation functions were tangent sigmoid (tansig) and logarithmic sigmoid (logsig), learning rate was 0.4 and training performance goal was 10^{-6}. Different combinations of the number of hidden neurons and activation functions for the training of the neural network architecture were actually used to have the optimum number of hidden neurons. Key curves among other classical formulas yielded the most effective (flow-sediment yield) for the whole observed sediment data for each station in which investigation was conducted are seen on Figure 5. Figure 6 is drawn for 2102 numbered station, Figure 7 for 2115, Figure 8 for 2119, Figure 9 for 2133 and finally, Figure 10 for 2145.

The calculated sediment values (calculated by using

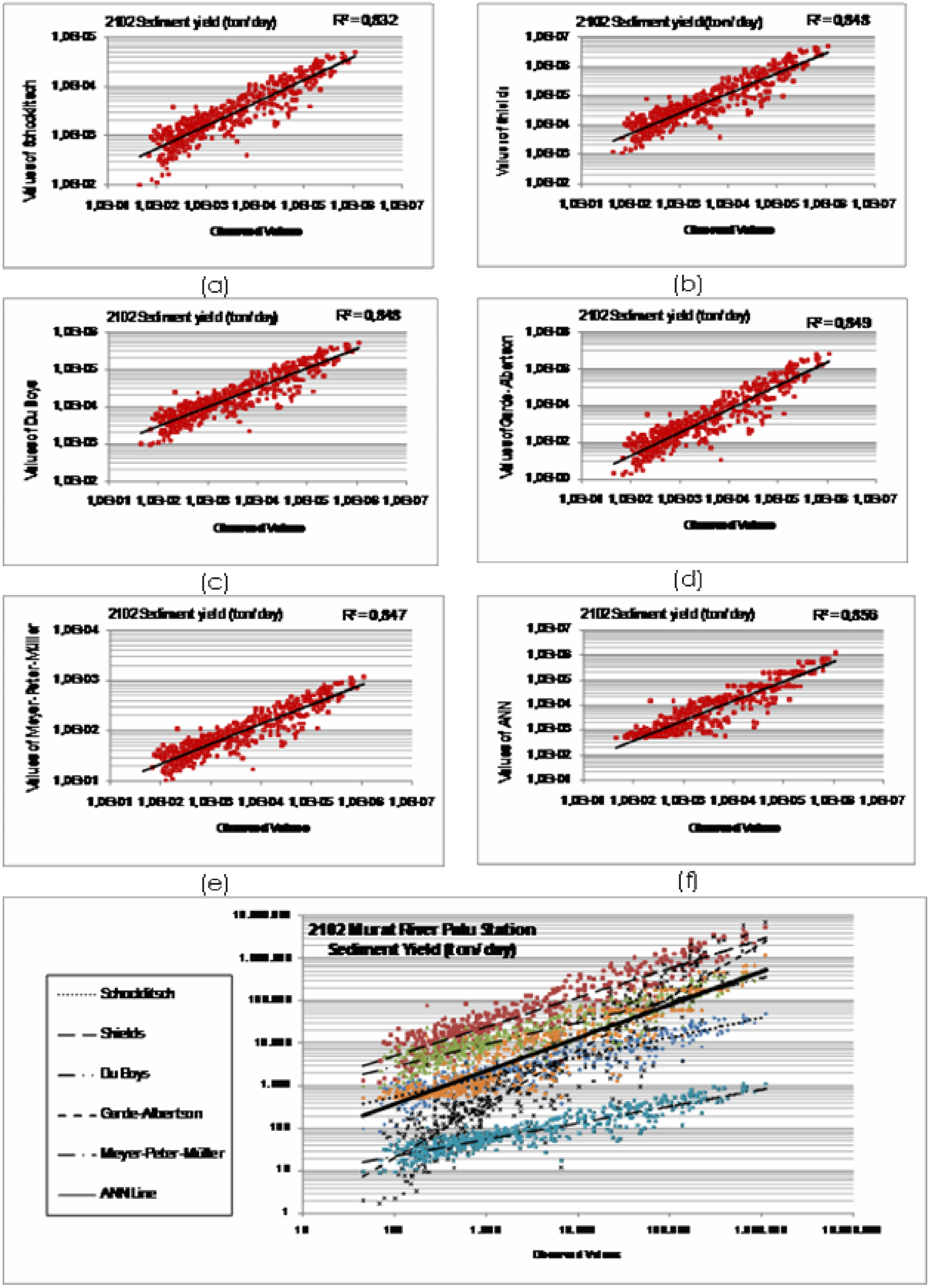

Figure 6. Calculated values of sediment yields of 2102 station with (a) Schoklitsch, (b) Shields, (c)Du Boys, (d) Garde-Albertson, (e) Meyer-Peter-Müller, (f) ANN formulas and (g) integrated schema for all methods.

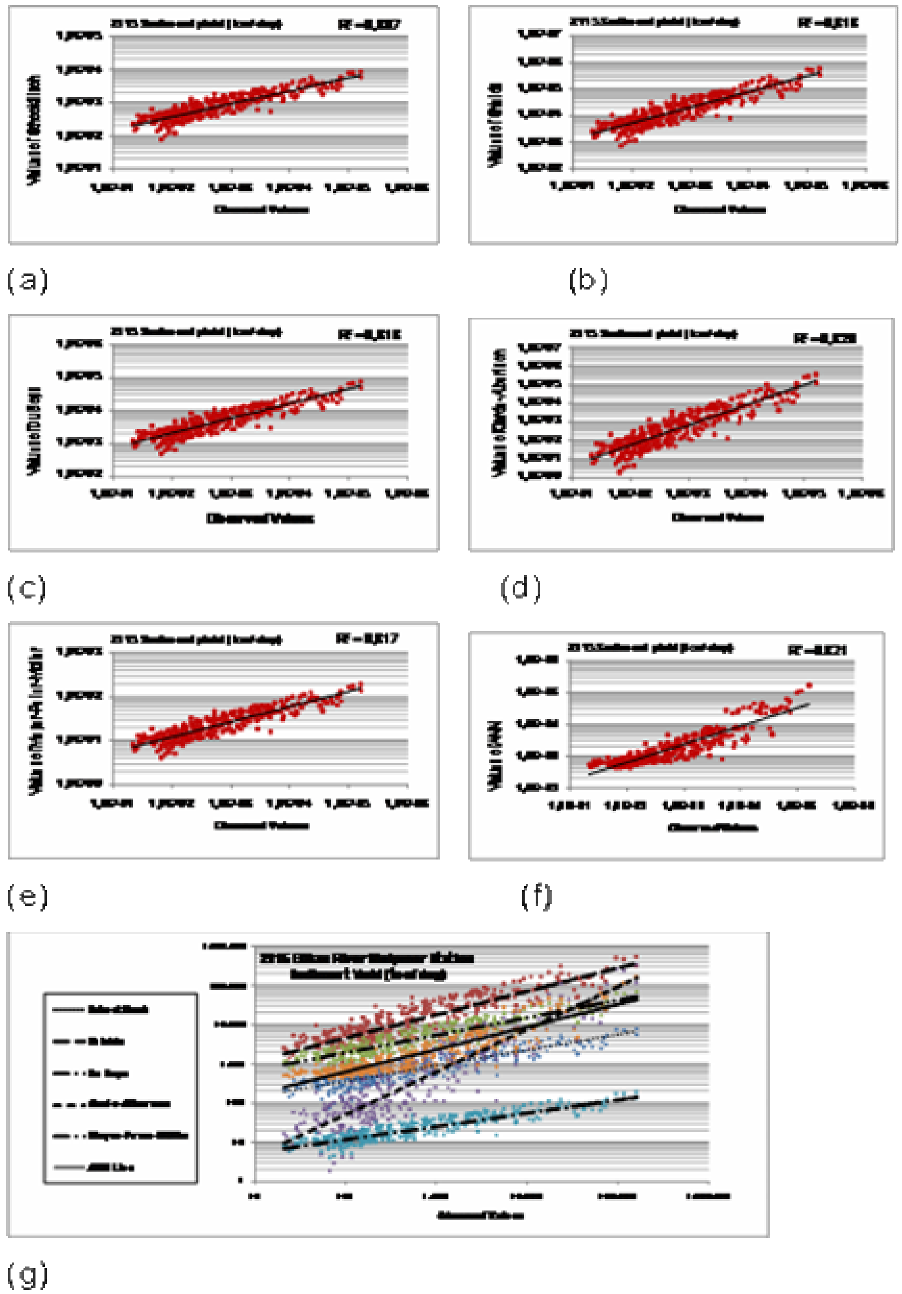

Figure 7. Calculated values of sediment yields of 2115 station with (a) Schoklitsch, (b) Shields, (c) Du Boys, (d) Garde-Albertson, (e) Meyer-Peter-Müller, (f) ANN formulas and (g) integrated schema for all methods.

Schoklitsch, Shields, Du Boys, Garde-Albertson, Meyer-Peter-Müller and ANN) for the stations are shown in the graphics of (a), (b), (c), (d), (e) and (f) in the relevant figures. Comparative graphic of all these methods is given by (g). Statistical R^2, RMSE and MAE parameters are seen on Table 3 and they show how the correlation between the observed sediment amounts and those estimated by using the formulas is strong. According to this, sediment values calculated using ANN have the highest R^2 parameter (0.8565 for 2102, 0.8217 for 2115, 0.8185 for 2119, 0.7990 for 2133 and 0.7344 for 2145), lowest RMSE values (0.42753 for 2102, 0.06437 for 2115, 0.09734 for 2133 and 0.00512 for 2145) and the lowest MAE values (0.16579 for 2102, 0.02647 for 2115, 0.03985 for 2119, 0.01973 for 2133 and 0.00231 for 2145) for all stations. Only one value (0.03847 for station 2119) obtained lower for Garde Albertson formula. The scattered plots of graphics (c) and (e) are more suitable than graphic (f) in Figure 7 and R^2 values seemed similar. Although the error value of some data in graphic (f)

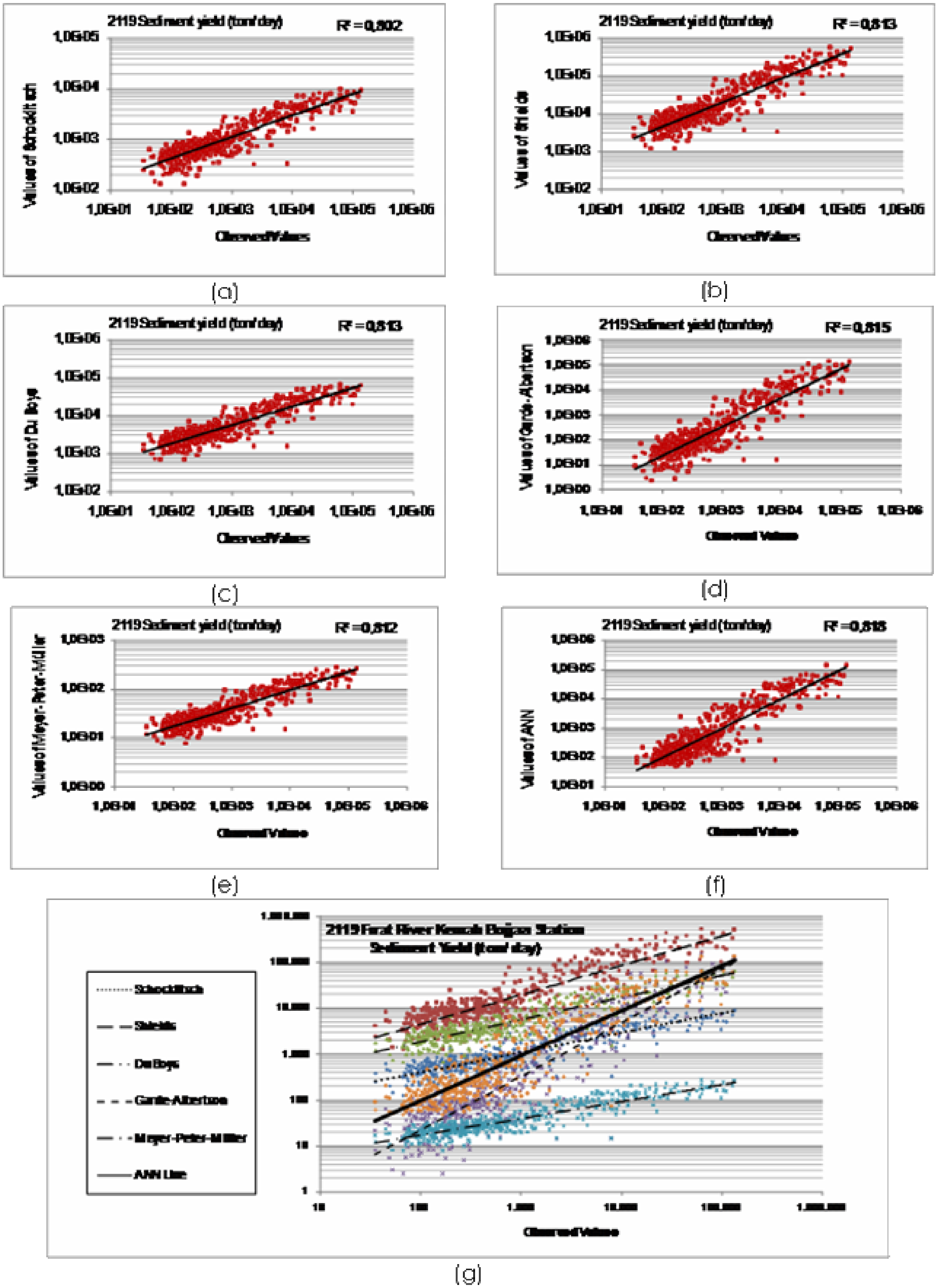

Figure 8. Calculated values of sediment yields of 2119 station with (a) Schoklitsch, (b) Shields, (c)Du Boys, (d) Garde-Albertson, (e) Meyer-Peter-Müller, (f) ANN formulas and (g) integrated schema for all methods.

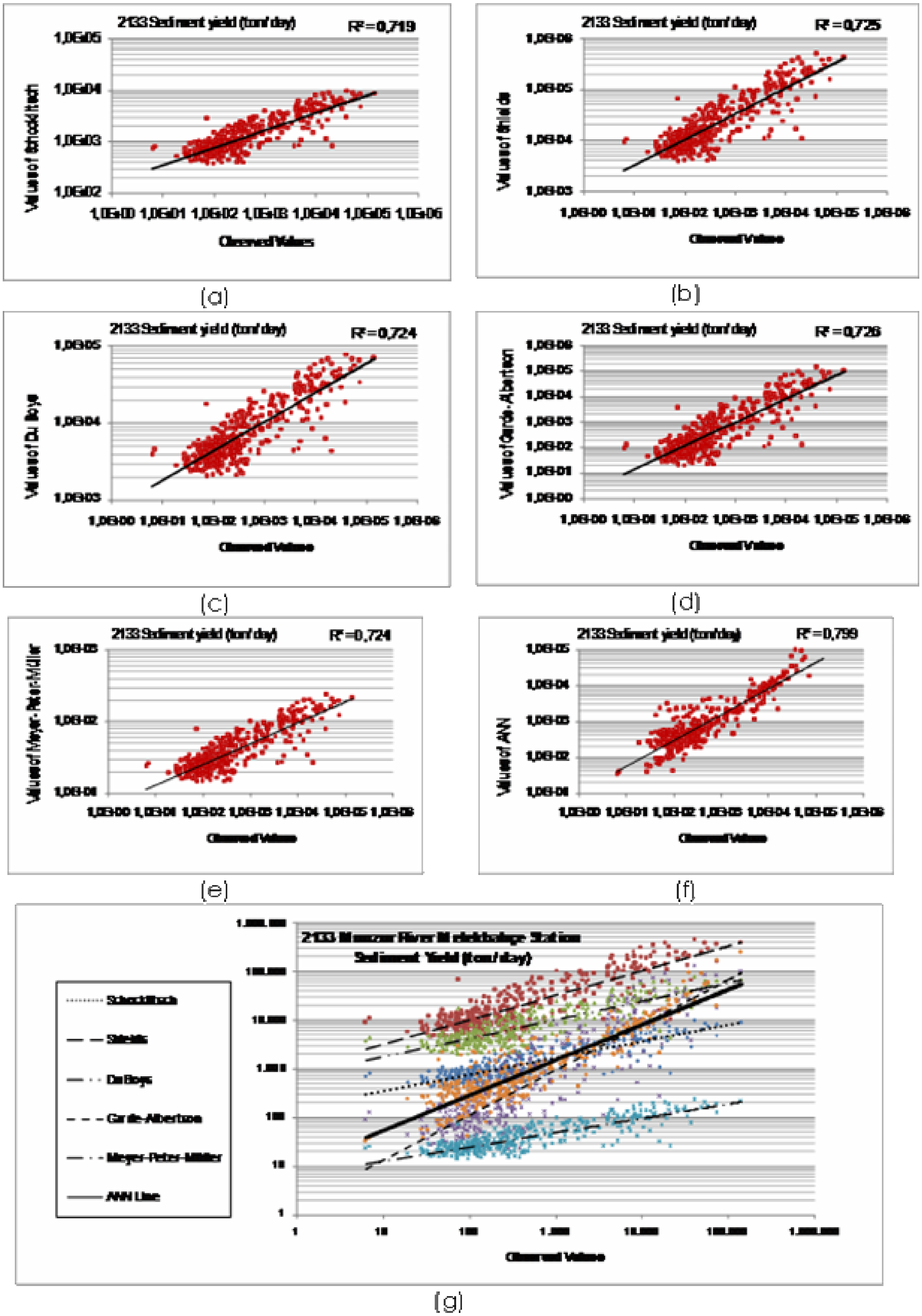

Figure 9. Calculated values of sediment yields of 2133 station with (a) Schoklitsch, (b) Shields, (c)Du Boys, (d) Garde-Albertson, (e) Meyer-Peter-Müller, (f) ANN formulas and (g) integrated schema for all methods.

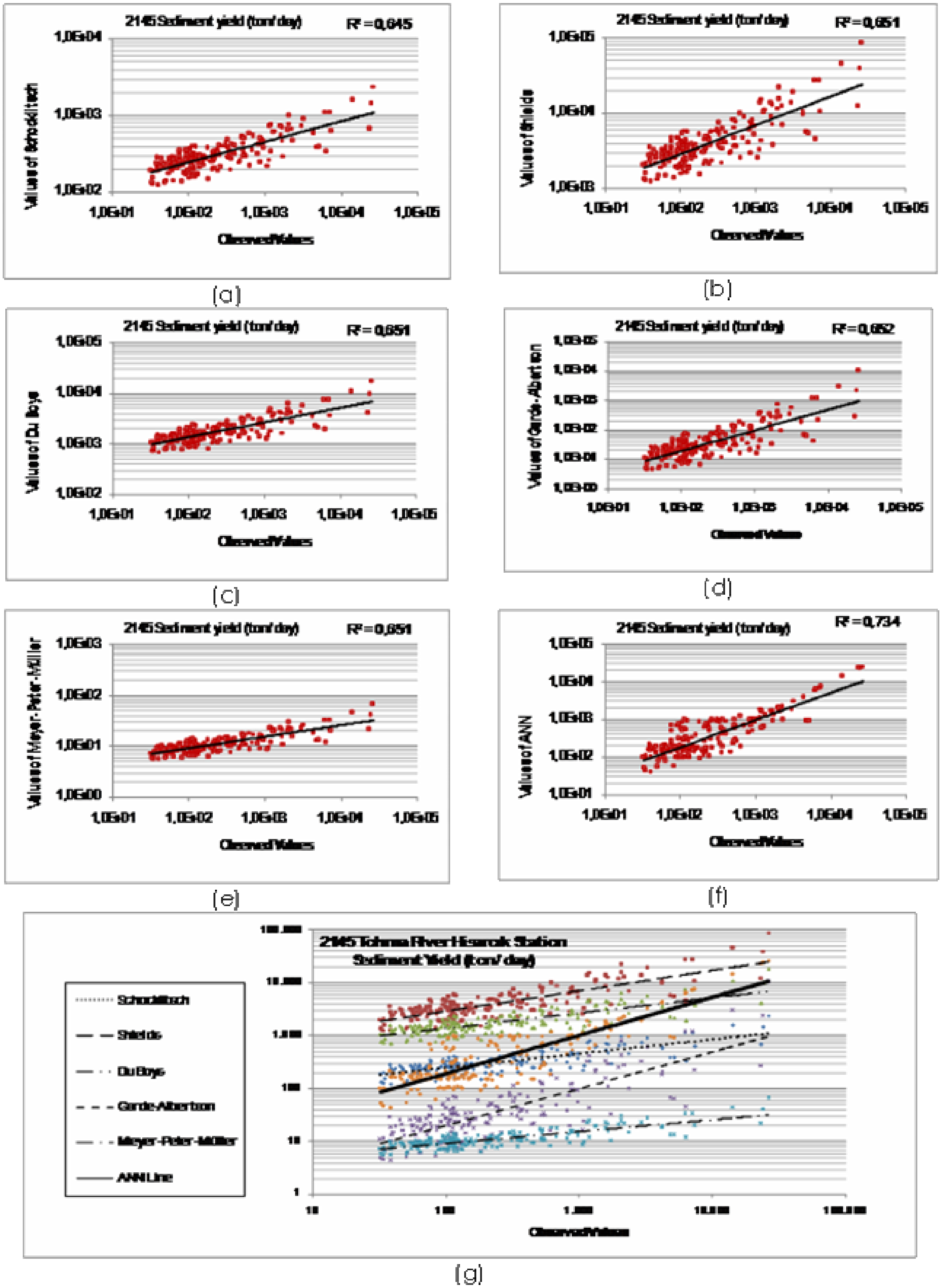

Figure 10. Calculated values of sediment yields of 2145 station with (a) Schoklitsch, (b) Shields, (c) Du Boys, (d) Garde-Albertson, (e) Meyer-Peter-Müller, (f) ANN formulas and (g) integrated schema for all methods.

Table 3. R^2, RMSE and MAE values obtained from classical equations and ANN application.

Used methods / stations		2102	2115	2119	2133	2145
Schoklitsch	**R^2**	**0.8326**	**0.8075**	**0.8029**	**0.7190**	**0.6450**
	RMSE	1.07978	0.17979	0.16836	0.11058	0.03217
	MAE	0.33503	0.04981	0.05111	0.03385	0.00876
Shields	R^2	0.8482	0.8187	0.8137	0.7252	0.6517
	RMSE	5.60832	0.58624	0.81587	0.81987	0.07267
	MAE	2.22345	0.30234	0.41303	0.45909	0.04663
Du Boys	R^2	0.8480	0.8182	0.8132	0.7249	0.6514
	RMSE	0.59465	0.11944	0.11904	0.13057	0.02425
	MAE	0.25865	0.06161	0.06613	0.09236	0.01660
Garde Albertson	R^2	0.8495	0.8203	0.8153	0.7262	0.6524
	RMSE	4.73473	0.17619	0.12226	0.10700	0.02947
	MAE	0.99371	0.04413	0.03847	0.03384	0.00891
Meyer-Peter- Müller	R^2	0.8471	0.8172	0.8122	0.7243	0.6510
	RMSE	1.15570	0.19132	0.18464	0.12620	0.03487
	MAE	0.37877	0.05719	0.06146	0.04004	0.01031
ANN	R^2	0.8565	0.8217	0.8185	0.7990	0.7344
	RMSE	0.42753	0.06437	0.11117	0.09734	0.00512
	MAE	0.16579	0.02647	0.03985	0.01973	0.00231

* RMSE and MAE values have to multiplied by 10^5.

seems irregularly distributed, most of the data give better error value than graphics (c) and (e).

Conclusion

In this study, a two-stage calculation was conducted to determine sediment amount, which is the most important parameter designating lifecycle of the most important dams built in Euphrates Basin, which is the largest basin in Turkey. At the first stage, estimations were conducted by using classical-empiric formulas. At the second stage, a new estimation mechanism was constructed by using ANN, having developed the network architecture. Then, the results were compared with previous ones. In the sediment estimations, Garde-Albertson's equation result for all stations under investigation according to the R^2 parameters. This was followed by Shields. On the other hand, Du Boys for RMSE and Schoklitsch and Garde-Albertson for MAE gave better values. However, ANN results yielded the best values for the five stations compared with the five classical formulas. Selecting the network architecture given in detail above has played a role in achieving this result.

However, this should not be ignored so as to think that reliability on these formulations shall not disappear in near future, because the classical formulas have high R^2 values and work with high performance at the sediment point of the existing dams, whose dead volumes were calculated with the help of these formulas. On the other hand, it is seen that an ANN approach can provide information about the structure of events (for example, the effect of antecedent conditions) which is impossible to achieve with sediment curves. This study indicates the ability of the multilayer feedforward backpropagation neural network model as a good technique for determining the sediment yield. The ANN model performs sufficiently well in the estimation of sediment. It is unavoidable putting ANN forward in such estimation studies, because it can produce result with no need of complex differential equations. Furthermore, estimating the capacity of mathematical data obtained with the help of experimental observations in limited number is restricted due to their nature. Moreover, ANNs may be applied to many different problems because its transfer function is not linear. ANN can be adapted to the nature of a problem directly. On the other hand, in addition to the mentioned advantages of ANN, the number of the stations and their statistically sufficient data providing capacity (long-term and large data are available for comparison), increases effectiveness and reliability of the obtained results. The study evidenced that the use of

ANN method yielded highly good results in modeling monthly sediment amounts carried along Euphrates River. It was evidenced that sediment amounts may be estimated by using flow amounts as input. Classical equations have been used in estimating sediment and reservoir dead volume has been designed depending on it. However, more realistic results may be achieved by using ANN method and also, when sediment measurement cannot be conducted for a certain period, the measured flow rates may be used as input in ANN model. As a result, sediment yields for the absent period may be estimated with a little error. Sediment transport is a complex phenomenon that is not clearly described in mathematical expressions up to date. Because of its nature of nonlinear architecture, ANN method may be a good alternative that can be used for sediment estimation. By utilising the neural network model, reasonable predictions can be made for the sediment yield. An ANN model can be constructed in order to provide a quick and dependable means of predicting the sediment. R^2 used current methodology, shows the general trend of a dynamic process. A detail investigation such as sedimentograph analysis on high/low flow may improve the quality of the outcome. Additional work is convenient with more data from various areas in order to strengthen these conclusions.

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