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By
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Theme:

CONTRIBUTION TO THE CHARACTERIZATION AND THE MODELLING OF SEDIMENT TRANSPORT IN URBAN HYDRO-SYSTEMS

Presented on 20/04/2017 in the front of the following doctoral committee:

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ملخص

في إدارة موارد المياه في النظم الهيدرولوجية المختلفة من المهم التقييم والتنبؤ لحمولة الرواسب في الأنهار. ومن الصعب الحصول على تقدير فعال وسريع لتحميل الرواسب عن طريق الشبكة العصبونية الاصطناعية دون تجنب الإفراط المناسب للبيانات في فترة التدريب وتحتوي هذه الأطروحة الحالية ثلاث خطوات من أجل الحصول على نماذج جيدة من الشبكات العصبونية الاصطناعية. الخطوة الأولى في هده الدراسة تضم المقارنة بين الشبكة العصبونية البسيطة متعددة الطبقات والشبكة العصبونية المنظمة باستخدام تقنية التوقف عن التدريب في وقت مبكر لتقدير وتوقع حمولة الرواسب في واد إيسر، الذي يقع في اعلى سد بني عمران، شمال الجزائر. وقد أجريت الدراسة اعتمادا على معطيات تدفق الرواسب وتدفق المياه عن طريق البيانات اليومية لمدة 30 عاما من 1971 الى 2001. في الخطوة الثانية تم استخدام نفس النماذج المستعملة في الخطوة الاولى و هي مقارنة الشبكة العصبونية البسيطة الشبكة العصبونية المنظمة باستخدام تقنية التوقف عن التدريب لحساب الرواسب العالقة في واد سيباعو منطقة القبائل الكبرى شمال الجزائر. وقد أجريت الدراسة على بيانات اليومية لتدفق المياه و الرواسب في الفترة ما بين 8 سنوات بين عامي 1971-1988 . تم تقييم كل من الدراسات على النهرين المدكورين اعلاه، بالمقارنة بين نتائج الشبكات العصبية البسيطة والشبكة المنضمة لقياس الرواسب في نهرين مختلفين.التطبيق قيم عن طريق مقياسين مختلفين الاول معامل التحديد و التاني جذر مربع متوسط الخطأ. أشارت نتائج المقارنة أن الشبكة العصبونية باستخدام تقنية التوقف عن التدريب في وقت مبكر لتجنب الافراط في التدريب في الوقت المناسب اعطت نتائج أفضل من الشبكات البسيطة في كل المناطق التي تمت دراستها، مع إعطاء أولوية للنتائج في واد إيسار. وأظهرت النتائج أن الافراط في التدريب الدي يحدث في الشبكات البسيطة يحدث بسبب تعقيد البيانات التي أدخلت على الشبكة. في الخطوة الثالثة حاولنا تأكيد كفاءة نموذج الشبكة العصبية باستخدام تقنية توقيف التدريب في وقت مبكر، وتطبيق نموذج الشبكة العصبونية لقياس تصريف الرواسب العالقة في النهر. وقد طبقت الدراسة على موقعين مختلفين، أولا، استخدمنا البيانات المدخلة من واد إيسار للتنبؤ للرواسب العالقة في نهر سيباعو، التي تقوم على بيانات تدفق اليومي للمياه و الرواسب .و تم استخدام البيانات اليومية لمدة 6 سنوات باستخدام بيانات التدريب لنهر إيسر، وسنتين من أجل اختبارالنموذج اعتمادا على بيانات من نفس الواد (واد سيباعو). ثانيا، استخدمنا البيانات المدخلة من واد سيباعو للتنبؤ للرواسب المتدفقة في نهر إيسار مع نفس البيانات مقسمة على نحو النمودج السابق على واد سيباعو. أشارت نتائج المقارنة أن الإفراط في التدريب وقع كثيرا في نماذجنا، وأظهرت تقنية التوقف عن التدريب في وقت مبكر قيم ضعيفة مقارنة مع التطبيقات باستخدام بيانات الواد الحقيقي التي عرضت في الخطوات الأولى والثانية. استخدام الشبكات العصبونية لتوقع الرواسب المصرفة في الواد اعطت نتائج متوسطة عند تجنب الإفراط في التدريب في نماذجنا.

الكلمات الدالة الشبكة العصبونية، تقنبة التوقف عن الدريب، واد ايسار، المصب، واد سيباعو، الرواسب، تدفق المياه، الجزائر، بني عمران، منطقة القبائل الكبرى.

RESUME:
La gestion des ressources en eau dans des différents systèmes hydrographiques, implique l'évaluation et la prédiction de la charge sédimentaire. Cette opération est difficile à réaliser en utilisant les réseaux de neurones, car on se heurte le plus souvent au problème de sur-ajustement des données d'apprentissage. La présente thèse, a pour objectif la proposition d'un modèle basé réseaux de neurones, ce dernier permet une estimation efficace et rapide de la charge sédimentaire dans deux bassins ; le bassin d'Isser et le bassin de Sebaou. L'approche proposée se compose de trois étapes ; La première étape consiste à comparer deux techniques différentes de réseau de neurones multicouches, à savoir, une avec un réseau neuronal non-régularisé et l'autre avec un réseau neuronal régularisé en utilisant la technique d'arrêt prématuré. Cette comparaison a été portée en premier lieu sur la rivière Isser, en amont du barrage Beni Amran, au nord de l'Algérie, en utilisant 30 ans de données quotidiennes de débits solides et liquides (1971-2001). Dans la deuxième étape, on a comparé les mêmes techniques de réseaux de neurones, mais cette fois elles ont été appliquées au cas de la rivière Sebaou à l'aval du barrage Takseb ; unique barrage dans le bassin versant de la Grande Kabylie. L'analyse a été effectuée en considérant les débits journaliers liquides et solides enregistrés dans une période de 9 ans (1978- 1987). Les deux techniques ont été évaluées et comparées à l'aide du coefficient de détermination (R^2) et l'erreur quadratique moyenne (RMSE). Les résultats obtenues à l'issu de ces deux étapes indiquent que le réseau de neurone régularisé par le critère d'arrêt prématuré donne de meilleurs résultats et ce, dans les deux zones étudiées, on constate également que cette technique donne de meilleurs résultats dans le cas de la rivière d'Isser. Les résultats montrent que le sur-ajustement de la retro-propagation se produit en raison de la complexité des données introduites dans le réseau. Dans la troisième étape, nous avons confirmé l'efficacité du modèle de réseau neuronal régularisé par la technique de l'arrêt prématuré dans le cas d'une rivière non-jaugée en utilisant les données d'un bassin voisin. Les données de la rivière Isser ont été utilisées pour prédire la charge sédimentaire dans la rivière Sebaou ensuite on a fait l'inverse. Les résultats montrent que l'utilisation du réseau de neurone non régularisé entraine de considérables erreurs de sur-ajustement dans le cas d'une rivière non-jaugée tandis que le modèle régularisé par le critère d'arrêt prématuré donne des résultats faibles même comparer aux mesures réelles. L'utilisation du réseau de neurones avec la technique d'arrêt prématuré dans la prévision de décharge de sédiments donne des résultats moyenne par condition d'éviter le phénomène de sur-apprentissage.

Mots Clé : Réseaux de neurones, Transport du sédiment, Débit liquide, arrêt prématuré, Bassin versant, Isser, Barrage, Sebaou, Oued, Bassin non jaugé, Algerie, Beni Amrane, Taksebt.

ABSTRACT

In the management of water resources in different hydro- systems it is important to evaluate and predict the sediment load in rivers. It is difficult to obtain an effective and fast estimation of sediment load by Artificial Neural Network without avoiding over-fitting of the training data. The presented thesis comprises of three steps in order to obtain an Artificial Neural Network model. In the first step the study comprises the comparison of a multi-layer perception network one with non-regularized network and the other with regularized network using the Early Stopping technique to estimate and forecast suspended sediment load in the Isser River, upstream of Beni Amran reservoir, northern Algeria. The study was carried out on daily sediment discharge and water discharge data of 30 years (1971–2001). In the second step, the author used the same Artificial Neural Network model once again, using non regularized and then regularized model to forecast suspended sediment in the Sebaou Wadi, in the Great Kabyle watershed, northern Algeria. The study was conducted on daily water and sediment discharge data of 9 years between (1978 and 1987). Both studies on different valleys were compared using the regularized and non regularized neural networks. The models were evaluated in terms of the Coefficient of Determination (R^2) and the Root Mean Square Error (RMSE). The comparison results indicated that the regularizing neural network using the Early Stopping criterion to avoid over fitting performs better than the non regularized networks in both studied areas, with a priority of a better performance values to the application of the Isser Wadi. The results show that the overtraining in the back propagation occurs because of the complexity of the data introduced to the network.

In the third step authors tried to confirm the efficiency of their neural network model using the Early Stopping technique, the application of the neural network model was the prediction of suspended sediment discharge in un-gauged river. The study was applied on two different sites, firstly, we used the input data of the Isser Wadi to forecast the suspended sediment in the Sebaou Wadi, carried on daily water and sediment discharge in a period of 9 years (7 years using training inputs from the Isser Wadi, and two years for validation and testing depending on the data of the Sebaou Wadi). Secondly, we used the input data of the Sebaou Wadi to forecast the sediment discharge of the Isser Wadi during the period of 9 years with the same divided data sets as the previous application on the Sebaou Wadi. The comparison of the results indicated that the over-fitting occurred often in our models, and the Early Stopping technique showed acceptable values but still further from the applications using real river data that were shown in the first and second steps. The use of the early stopping technique in forecasting sediment discharge is very effective and robust especially to avoid the over-fitting that occurred often in our models.

Keywords: Artificial neural network, Suspended sediment, Back propagation, Water discharge, Erosion, Early stopping, Isser, Sebaou, Algeria, Wadi, Watershed, Dam, Ungauged river, Beni Amran, Taksebt.

SOMMAIRE

LIST OF FIGURES

LISTE OF TABLES

NOTIFICATIONS

SSD: Suspended Sediment Discharge
SSD_{t-1}: Previous Suspended Sediment Discharge
SSD_{t-2}: Two Previous Suspended Sediment Discharge
WD: Water Discharge
WD_{t-1}: Previous Water Discharge
ANN: Artificial Neural Network
NN: Neural Network
BP: Back Propagation
MLP: Multi Layer Perceptron
FFBPNN: Feed Forward Back Propagation Neural Network
FTDNN: Focused Time Delay Neural Network
RBFNN: Radial Basis Function Neural Network
CCNN: Cascade Correlation Neural network
RNN: Recurrent Neural Network
SNFR: Signal to Noise Ratio Figure.
ΣLi: The sum of Thalwegs in the watershed
ΣN1: The number of Perennial streams
Dd: Drainage density
F1: The stream's order of the main stem
Ct: The factor of the torrential nature of rainfall
ANRH: National Agency of Hydric Resources
STD: Standard Deviation
MIN: Minimum
MAX: Maximum
R^2: Coefficient of Determination
RMSE: Root Mean Square Error
MLR: Multiple Linear Regressions
MNLR: Multiple Non-Linear Regressions
ARIMA: Auto-Regressive Integrated Moving Average
GD: Gradient Decent
GDM: Gradient Descent with Momentum
SCG: Sealed Conjugate Gradient
LM: Levenberg Marquadt
USLE: Universal Soil Loss Equation
RUSLE: Revised Universal Soil Loss Equation
MUSLE: Modification of Universal Soil Loss Equation
WEPP: Water Erosion Prediction Project
SRC: Sediment Rating Curve.

I. INTRODUCTION

Among the most critical environmental risks that hydrologists are dealing with nowadays is sediment load in watersheds. Sedimentation in rivers, watersheds and dams is a serious problem Tachi et al., (2016). The ecosystems can be damaged by sedimentation that is carried by the runoff when the quantity is high.

The cost can be measured in financial terms. It can also be considered in respect of our need to handle limited water resources for consumption, agriculture, fisheries, industrial activities or power generation Abrahart and White, (2001).

Suspended sediment discharge in a river is an important parameter for the management of hydraulic projects, and an index for the status of soil erosion and ecological environment of a catchment Zhu et al., (2007).

An effective and fast estimation of flow and flux in watersheds are ones of great interests for large number of engineering applications to protect hydraulic infrastructure from different disasters such as: stability problems, the loss of water storage in reservoir and the deterioration of water quality Tachi, et al., (2016).

The processes of flow and sediment load are complex in Algeria, due to rainfall regime which is infrequent, intense and occurs in the coastal band, as well as the shortage of data and the difficulty of daily direct measurement. According to (Remini, 2004; Remini et al., 2009) the erosion rate is between 2000 and 4000 t/km^2/year. The average annual amount of deposited sediment in dams passed from 20 million m3 in the 80's to 35 million m3 in the 90's and reached 45 million m3 in 2000 (Serbah, 2011). The suspended sediment discharge in Algeria is estimated at the hydrometric stations of watersheds for substantially all episodes of flow. The increase of suspended sediment load and its sedimentation in Algeria led hydrologists to research the phenomenon of suspended sediment discharge and its relation with some of the hydro-climatic parameters, such as rainfall, runoff, land cover, and sediment concentration in different valleys. We can cite couple of works: "Medinger (1960), who proceeded to the treatment of thirty basins of the first series of measures collected in Algeria during the period 1946 – 1957; Tixeront (1960), who based its research on the content of suspended sediment in Algerian and Tunisian Rivers with 32 and 9 hydrometric stations, respectively; Demmak (1984), who obtained an empirical relationship between sediment discharge and catchment physico-climatic parameters during period of 10 years in some of the northern watersheds in Algeria; Meddi et al (1998), who used in their work data of 18 reservoirs with 50 hydrometric stations in Algeria, 16 Moroccan reservoirs and 11 Tunisian reservoirs to improve a model which estimates suspended sediment load in northern Algeria. One can also note papers of; Walling et al., (1981), Demmak, (1982), Demmak, (1984), Touaibia et al., (2001), Meddi et al., (1999), Terfous, (2001), Benkhaled and Remini, (2003), Bouanani, (2005), Achite and Meddi, (2004, 2005), Lefkir et al., (2006), Larfi and Remini, (2006), Khanchoul, (2006,2009), Cherif et al., (2009) and Boucheklia et al., (2013), who have tried to quantify suspended sediment discharge and explain the phenomena of flow and suspended sediment load, and to highlight relationships between different climatic parameters which can be applied to regions or watersheds where measurements are rare or nonexistent. All these parameters differ from one author to another and from region to region. Each attempted to characterize the region or find some relation between different parameters and suspended sediment discharge using linear regression.

During the last twenty years hydrologists started applying artificial intelligence techniques to estimate and predict different hydrological phenomena. Among the techniques were: (ANFIS) Adaptive Neural Network Fuzzy Inference System (Bae et al., 2007; Kisi, 2005), (GP) Genetic Programme (Savic et al., 1999; Aytek and Kisi, 2008) and (ANN) Artificial Neural Network (ASCE 2000a, b; Abrahart et al., 2004; Solomatine et al., 2003; Zhu et al., 2007; Mellesse et al., 2011; Afan et al., 2014; Tachi et al., 2016).

Neural Networks are alternative and complementary sets of techniques to traditional models. NN can be described as a computational pattern searching and matching procedures that allow forecasting without detailed knowledge of the physical or chemical processes. For the hydrologists, this technique appeals considerable, provided the absence of a detailed process explanation that can be borne Abrahart et al., (2004).

ANN enriches hydrological modelling in many different ways. For example, it can approximate any arbitrary continuous functions, simulate a nonlinear system without a priori assumption of processes involved, and give a good solution even when input data are incomplete ASCE, (2000 a, b).

The last decade has seen the gradual introduction of informatics tools, such as artificial neural networks, into hydrology, hydrogeology and water resources planning and management. The applications of these techniques have been many and various, but a broad appreciation of their potential has been slow to develop Minns A.W and Hall M.J., (2004).

Studies in the hydrological forecasting context, have reported that it is probable for the artificial neural networks to give good alternative for rainfall–runoff modelling (Hsu et al., 1995; Savic et al., 1999; Solomatine & Dulal., 2003), stream flow prediction (Raman and Sunilkumar, 1995; Campolo et al, 1999; Kisi, 2004a), and reservoir inflow forecasting (Saad et al., 1996; Jain et al., 1999), as well as water quality assessment (Clair and Ehrman, 1998), the development of artificial neural networks went further in hydrology studying more difficult phenomenon such as sediment transport. The number of research papers wasn't as wide as rainfall-runoff, but it provided the estimation of sediment discharge comparing to the classical models that were used before to forecast sediment load. Many researchers contributed in forecasting of sediment load using Neural networks; Abrahart and White (2001) used ANN to predict suspended sediment load with rainfall and runoff as inputs, for a series of various land use and management regimes of four experimental catchments in Malawi, and indicated that the ANN approach could give a better fit to the data than multiple linear regression (MLR). Kisi (2004) indicated that the use of artificial neural network to forecast suspended sediment concentration in daily scale could show better performance results than other models. Raghuwanshi et al., (2006) compared ANN models with linear regression to predict runoff and sediment load on two different time scales (daily and weekly) in agricultural basin. And they stated that the ANN models showed better performance results than the linear regression models. Raveendra and Mathur (2008) confirmed the accuracy of the feed forward back propagation neural network model to quantify the sediment yield in watersheds.

Mellesse et al., (2011) compared Back Propagation neural network with Multiple Linear Regression (MLR), Multiple Non-Linear Regression (MNLR) and Auto-Regressive Integrated Moving Average (ARIMA) models in three different big rivers; Mississippi, Rio Grande and Missouri rivers in USA. The study was carried out on weekly and daily rainfall, sediment discharge, antecedent water discharge and antecedent sediment load to predict current sediment load. The study concluded that daily prediction was accurate than weekly. And the ANN model gave higher results than other regressive models. Afan et al., (2014) confirmed in their paper that the use of artificial neural network to predict sediment load is very accurate when depending on both previous sediment discharge and water discharge data. Recently hydrologists compared different artificial intelligence techniques encouraging the search for new methods to improve the ANN training and avoid the over-fitting that occurs in the networks. The over-training of the used data may result in deterioration of generalization properties of the model and when applied to novel measurements lead to its unreliable performance Piotrowski and Napiorkowski, (2013). The Early Stopping criterion is one of the most common methods used in artificial neural network to avoid over-fitting because of its simplicity of understanding and implementation Liu Yinyin et al., (2008); Prechlet, (1998).

Different researchers developed couple of techniques in Artificial Neural Network (ANN) for the improvement of neural network, and avoid any over fitting during the training period including; error regularization (Poggio and Girosi, 1990), Weight Decay and different variation of Cross Validation (Haykin, 1999), Noise Injection (Holmstrom and Koistinen, 1992), Optimized Approximation Algorithm (Liu et al, 2008) and the early stopping technique which is the used method in this research based on the researches of (Sjoberg and Ljung, 1992; Ammari et al., 1996; Prechlet, 1998; Orr and Müller, 1998; Khadir, 2005; and Piotrowski et al., 2014; Tachi et al., 2016).

For better effectiveness of sediment load estimation and different problems that happen in reservoirs, rivers, agricultures, etc because of erosion and sedimentation, we forecasted and estimated the suspended sediment discharge in the Isser and Sebaou rivers through the following steps.

In the First step:

We forecasted the sediment discharge of the Isser Wadi, upstream of Beni Amrane reservoir using regularized and non regularized neural networks.

In the second step:

We forecasted the sediment discharge of the Sebaou Wadi, downstream of Taksebt reservoir using regularized and non regularized neural networks.

In the third step:

We forecasted the sediment discharge of both valleys once again, this time using input data of Isser Wadi to Sebaou Wadi model and vice versa, and showing the efficacy of using neural network to estimate the sediment discharge in ungauged basin.

For better explanation, our thesis is constructed of five chapters in the given order:

The First chapter, Introduction, discusses the phenomena of sediment discharge, and gives an overview of the estimation of sediment discharge in Algeria, the use of ANN for estimating different hydrologic parameters in watersheds.

The second chapter is a brief description of the studied areas, both Isser and Sebaou watersheds, and detailed information about the reservoirs that are alimented by the studied rivers and their urban hydro systems.

The third chapter is an overview of the artificial neural network, its construction, and its application in hydrology and predicting the suspended sediment phenomenon.

The fourth chapter is an overview of the phenomenon of erosion and sedimentation.

The fifth chapter discuss the results, interpretation, and the comparison between results and different methods on different areas.

Finally the sixth chapter concludes the evaluation of our artificial neural network model forecasting suspended sediment discharge in both gauged and non gauged rivers, and giving the perspectives that will contribute the use of water resources and reduce losses in the aquatic systems.

II. THE STUDIED AREAS

II.1 INTRODUCTION:

This chapter presents the studied areas and the used data of two watersheds in northern Algeria. The measured data; water discharge and sediment concentration were taken from both valleys studied herein (Isser wadi and Sebaou wadi) from the hydrometric stations nomination that were constructed by the national agency of hydraulic resources; the Lakhdaria hydrometric station (090501), which controls the Isser watershed, and the Belloua hydrometric station (021803) which controls the Great Kabyle watershed.

II.2 THE ISSER WATERSHED:

II.2.1 The geographical situation:

The study area comprises the watershed of Isser that is located at 36°52′N~35°52′N and 3°56′E~2°52′E, northern Algeria in the upstream of Beni Amran reservoir. Its total area is 4140.9 km^2.

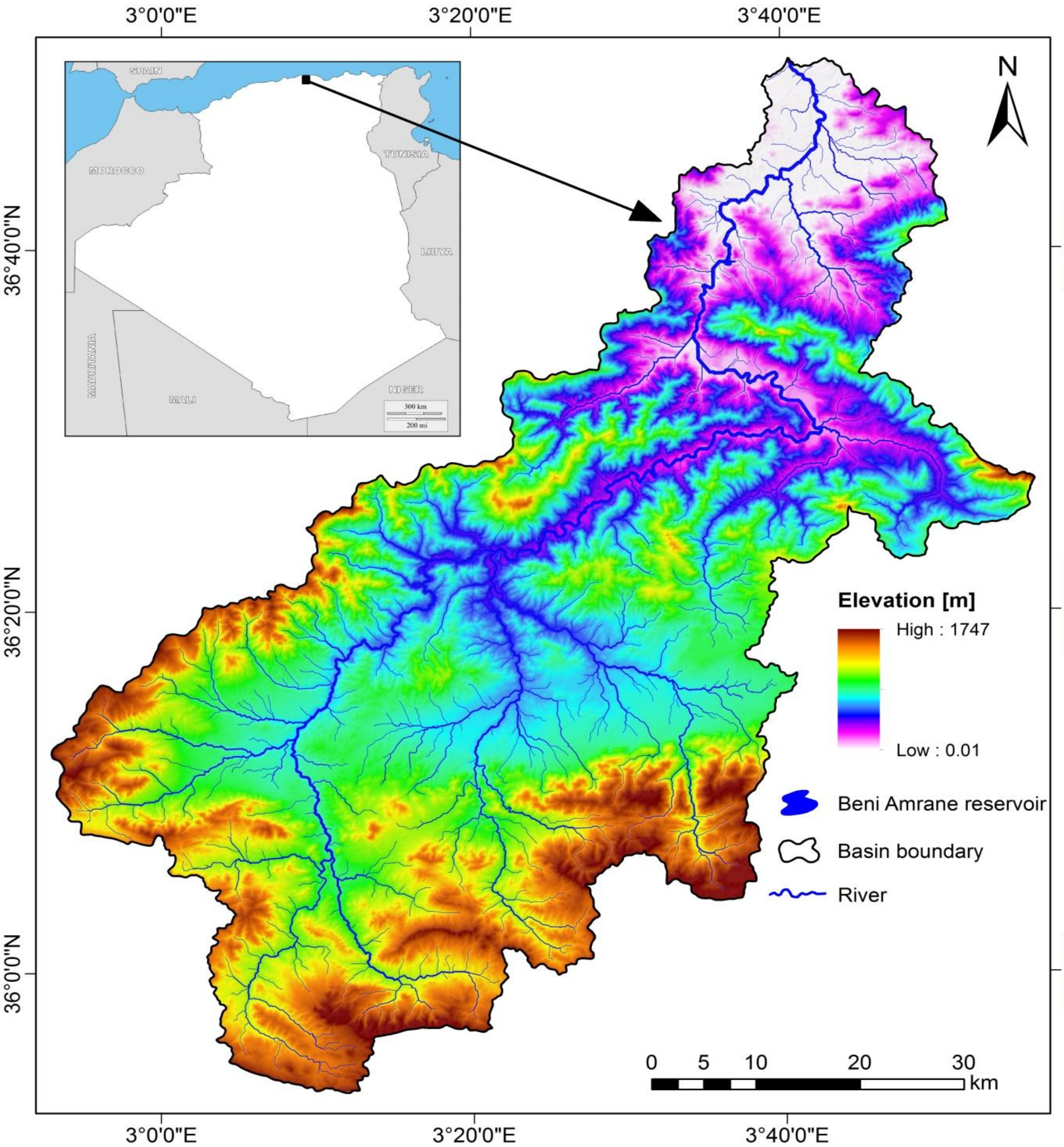


Figure II.1 The geographical situation of the Isser watershed in Algeria

II.2.2 The altitudes:

The watershed is located entirely in the mountains; its highest point is located at Jebel Dira on the southern east of the Isser watershed, with approximately 1747 m. Followed by Djbel Bou Sabat and Djbel Chaaba on the south, and the Djbel Guanntra and Mahouada located on the southern west of the watershed, going to the lowest point of the watershed which is located at the valley's outlet on the Mediterranean Sea. The average altitude of the basin is about 673 m.

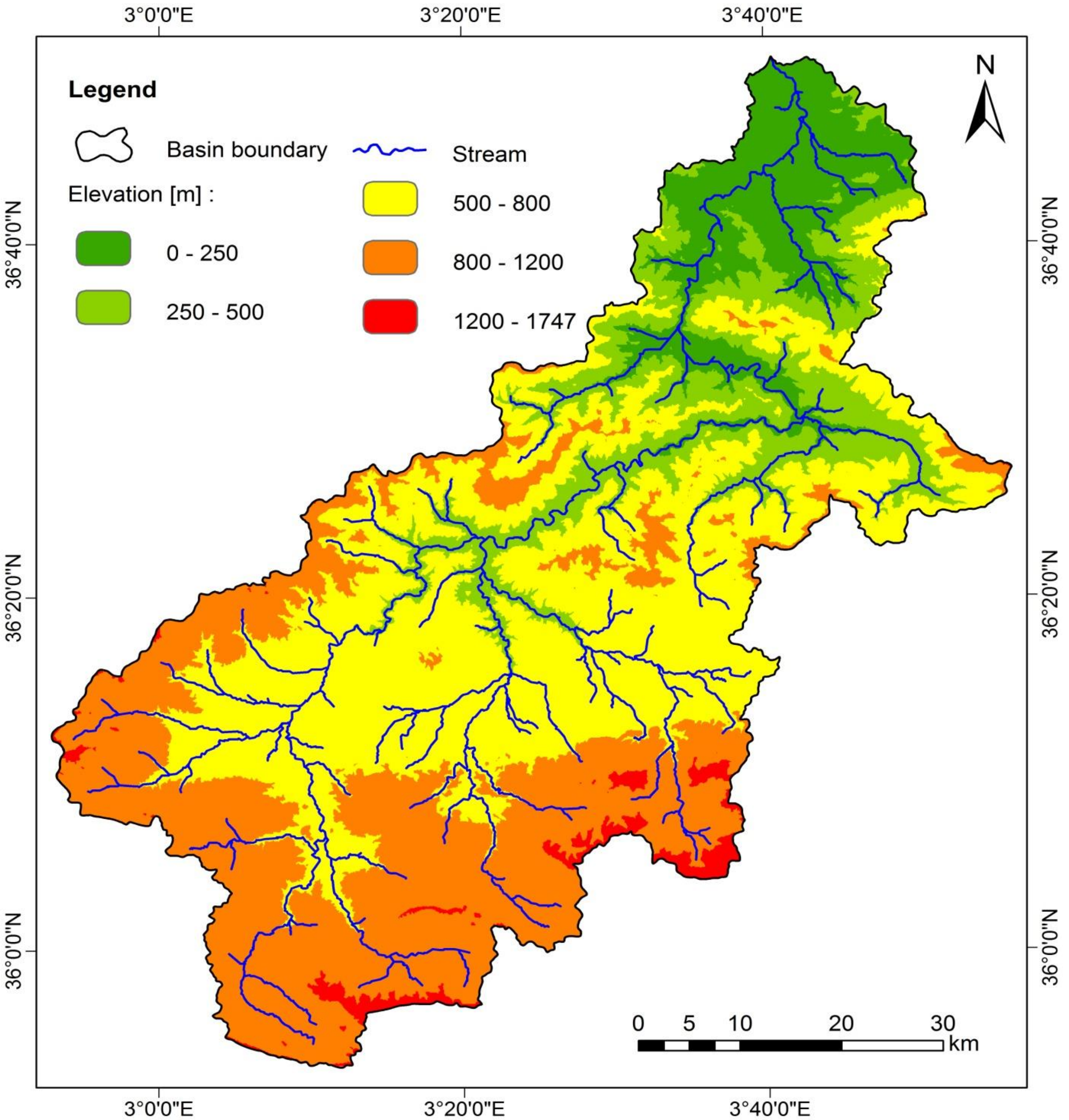


Figure II.2 Contour map of the Isser watershed.

II.2.3 The relief:

The basin is characterized by relatively steep slopes; more than 6% of the area; which is 267.67 Km² consists of slopes that are over 35%. More than 51% of the watershed areas are varying between slopes of 12% to 35%. More than 1743 km² is less than 12%.

Table II-1 The distribution of surfaces based on the elevation.

SLOPES [%]	AREA [Km²]	AREA [%]
< 3	348.97	8.43
3 - 7	646.51	15.61
7 - 12	749.89	18.11
12 - 20	1051.04	25.38
20 - 35	1077.36	26.01
> 35	267.67	6.46

The following figure II.3 explaines the distribution of surfaces on the Isser watershed based on the slopes, and we can notice from the figure that the high slopes are figured out in the medium Isser, which causes high erosion and soil degradation in this area.

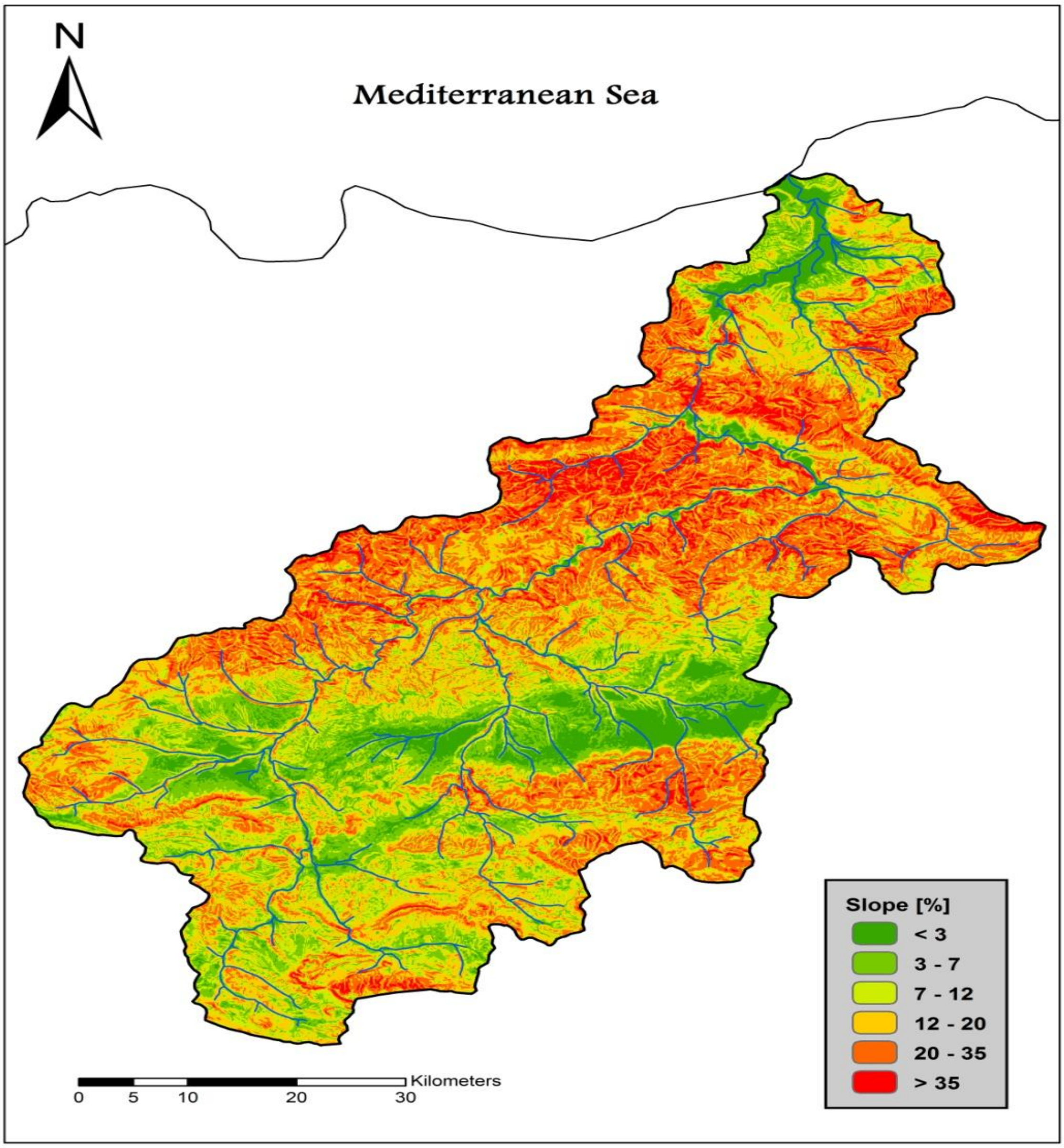


Figure II.3 The slopes map of the Isser watershed.

II.2.4 Hydrology:

The basin is prone to a Mediterranean climate with a sub-humid southern part and a humid northern part. The mean annual rainfall is estimated at 800mm/yr while the temperature averages 18.5°C per year. The Isser watershed is characterized by a dispersed valley system. The table bellow (Table II-2) summarizes the hydrological characteristics of the watershed.

Table II-2 The hydrological characteristics of the Isser watershed.

CHARACTERISTICS	VALUES
Area (Km^2)	4140.9
Perimeter (Km)	443
Average Rainfall (mm)	800
Max Elevation (m)	1747
Min Elevation (m)	0.01
Average Elevation (m)	673
River's Order	07
The sum of Thalwegs in watershed (Km)	3475
The number of perennial streams	1552
Drainage density (Km/Km^2)	0.84
The stream's order of the main stem	0.38
the factor of the torrential nature of rainfall	0.32

ΣLi, the sum of thalwegs in the watershed; $\Sigma N1$, the number of perennial streams; Dd, drainage density; F1, the stream's order of the main stem; Ct, the factor of the torrential nature of rainfall.

II.2.5 Water systems:

The Isser basin joins the great mountain range Kabyle and is separated by the Krachema massive into two perimeters: lower and upper Isser. The Isser Wadi is mainly controlled by six gauging stations; there are two main stations: Latreille upstream station and Lakhdaria downstream station, and four hydrometric stations in each sub-basin (Figure II.4).

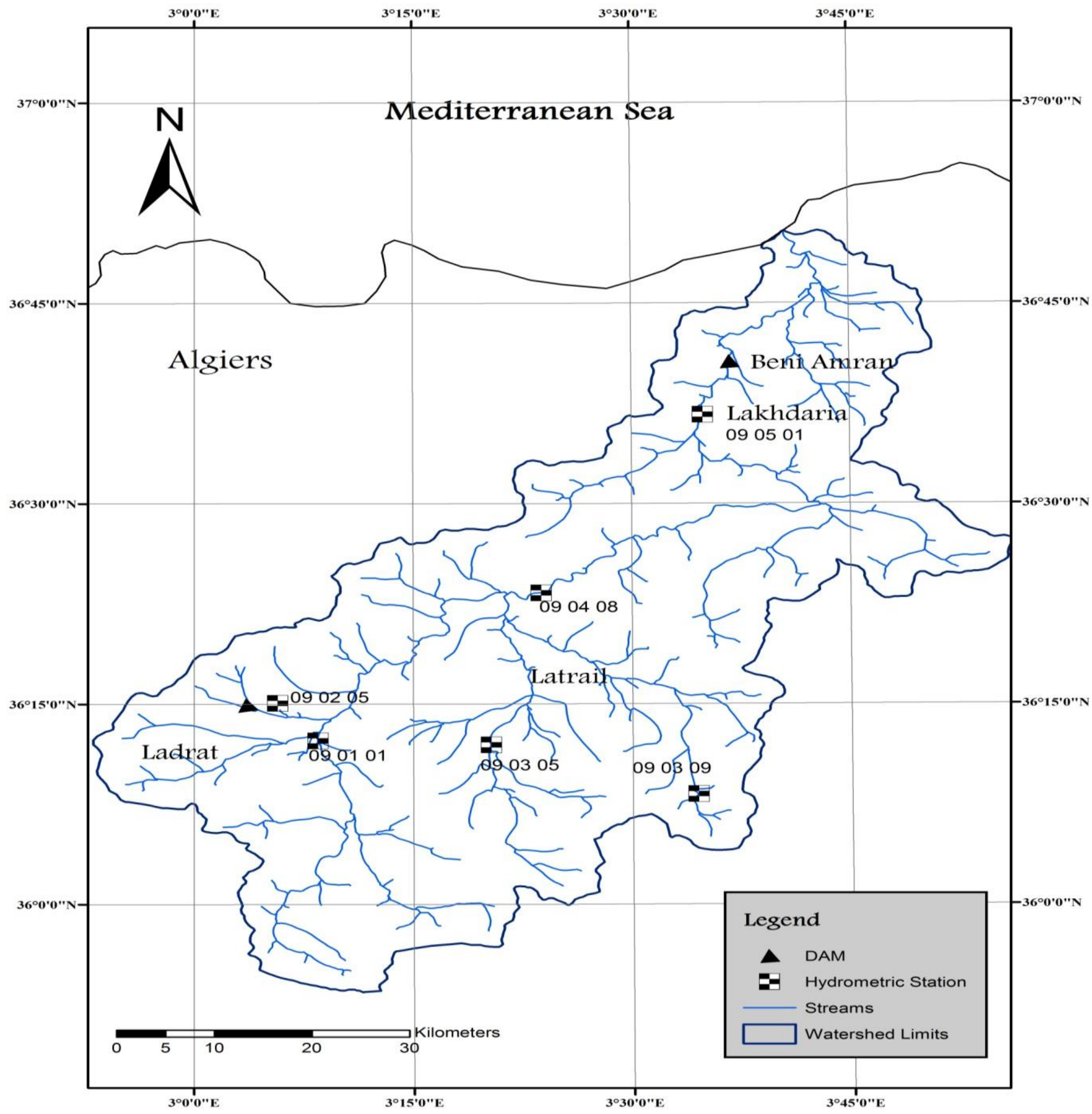


Figure II.4 map of the Isser Wadi and Lakhdaria hydrometric station.

II.2.6 Geology and morphology of the Isser watershed:

The region of the Isser watershed is characterized by different formations mainly dominated by unsaturated soil covering different watershed area, on the north going on the sides of the watershed to the western center and finishes in the southern part of the watershed as it is illustrated in the figure bellow (Figure II.5).The second dominant formation is the calcareous soil and it is located inside the northern, centre and southern part of the watershed limited outside by the unsaturated soil formation. The third formation is the balanced soil it is located in the southern part of the watershed. The alluvial soil formation it is founded mostly where is the Isser Wadi passes. The podzolic soil is located on the east southern.

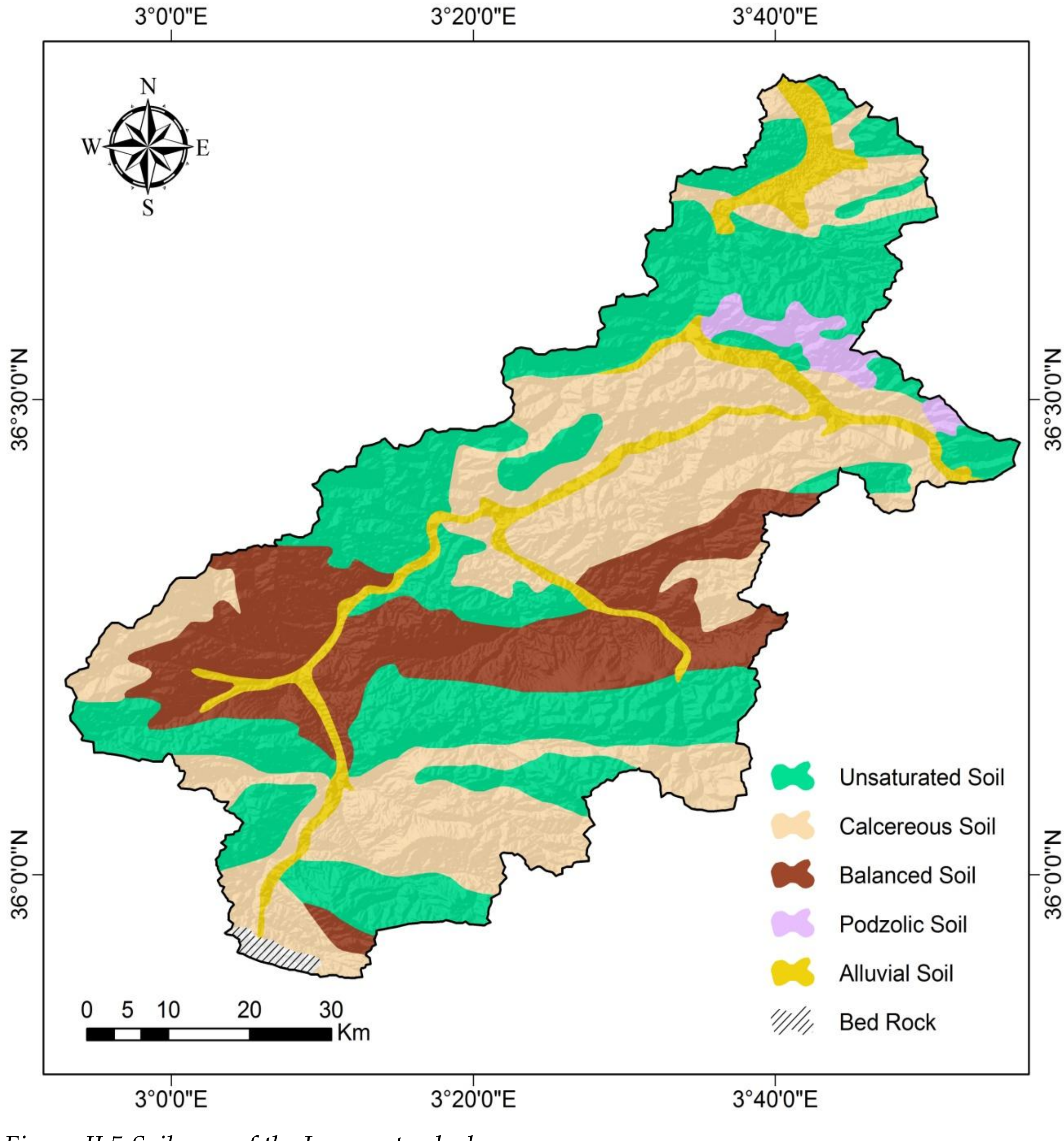


Figure II.5 Soil map of the Isser watershed.

II.2.7 The vegetal cover of the Isser watershed:

Regarding the vegetation cover map by the Landsat8 (Figure II.6), the basin is characterized by a low plant density, it represents about 25% of the total area, which speeds up the phenomenon of erosion (the erosion process), and the vegetation cover in the Isser watershed is concentrated in the north part around the Beni Amrane reservoir. The rest of areas represent mostly the crops which they have important factor in counting the erosion by different empirical formulas.

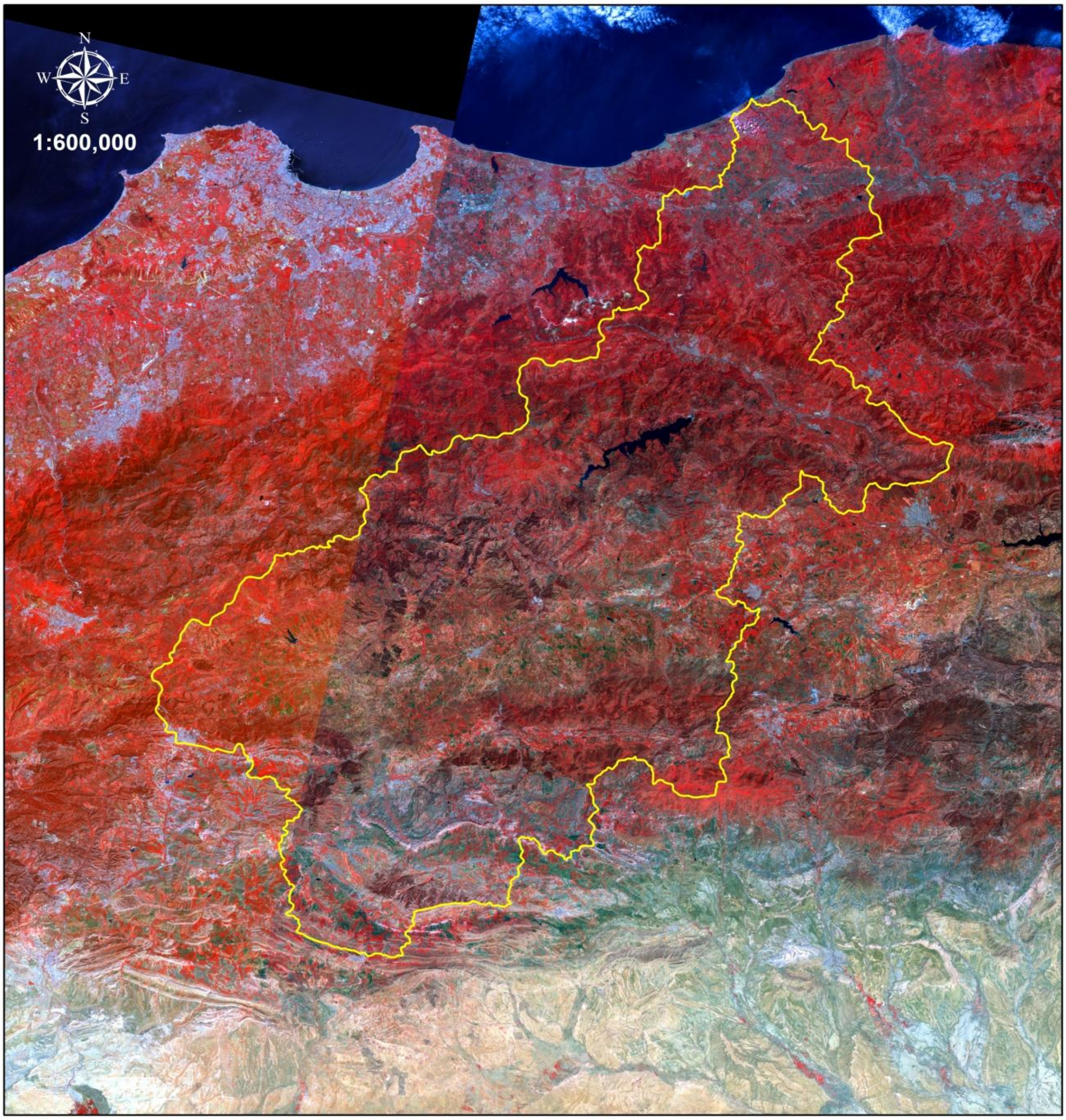


Figure II.6 The vegetation cover image by the Landsat8, bands combination 5, 4, and 2. Dated: 2014-05-07T17:24:31.

II.2.8 The Beni Amrane reservoir:

The Beni Amrane reservoir was built and put in service in 1988. The highest level of exceptional water is 76.1 m, and the dimension of the dam impoundment is set at

67.00 m. The dam was raised up in July, 2003, the initial normal impoundment was 63.00 m.

It can be noticed that the retaining of Beni Amrane reservoir represents a transfer round to the Keddara dam that supply the city of Algiers with drinking water. Therefore, the water quality in the Beni Amrane dam must be adequate to make transfers to the Keddara's dam. According to the National Agency of Water Resources ANRH, (2000), the concentration of suspended solids should be less than 2 g / L, to have good quality of drinking water from the Beni Amrane's reservoir to the Keddara's reservoir.

According to the survey of the bathymetric level of the dam, was conducted by the Algerian national agency of reservoirs in 2004, the registered volume of water was 11.85 Hm^3 in the normal impoundment 67 m, with an estimated impoundment surface was around 202.5 ha and with annual average silting of 4.10 Hm^3. The dimension of the highest water lever after bathymetric survey was 76.1 m, the volume of water was estimated at 35.17 Hm3 while the area was 303.3 ha. The following table summarizes the reservoir characteristics since commissioning to the first bathymetric survey in 2004 Lefkir, (2009).

Table II-3 The characteristics of the Beni Amrane's reservoir.

THE CHARACTERISTICS OF THE DAM	VALUES
The altitude of the river bed from the base of the dam.	38.0 m
The altitude of the spillway crests	63.5 m
The altitude of the dam crest.	77.5 m
The volume of the retained water	15.6 Mm^3
The length of the weir crest	102.5 m
The capacity of the spillway	10000 m^3/s
The altitude of the crest from the dam	77.5 m
The length of the dam	460.0 m
The altitude of the base	38 m
The level from the riverbed	40 m
The average annual silting	4.10 hm3/an

II.2.9 The database of the Isser Wadi:

The watershed of the Isser Wadi has a total area of 4140.9 km². The network of hydrometric measurements of Wadi Isser and its tributaries, implemented and managed by the ANRH, has a network of 7 gauging stations: El Omaria (091205), Dechmia (090309), Beni Slimane (090305), Mezahim (030191) Aoamar station (090416) la Traille (090408) and Lakhdaria (090501).

In general, the density of the tributaries is much dispersed compared to the vast expanse of the area. These stations data sets are generally incomplete, full of gaps or with outliers, except data for the last two stations; Traille and Lakhdaria.

II.2.10 The statistical data parameters:

To model the relationship between water and solid flow in the watershed of Isser, a data set consisting of several parameters was used. This series is mainly composed of daily water discharge and sediment discharge spanning a period of thirty hydrological years from 1st September 1971 to 31st August 2001. The used data in the presented study is divided into three sets: the training set which is used for learning process, the validation set was for the purpose of using the cross validation during the learning process and the testing set for testing and assessing the neural network developed model. This series was kindly, provided to us by ANRH concerns the Lakhdaria station (090501) upstream of the Beni Amrane Reservoir. The statistical parameters of the used data during these three sets (training, validation and testing) are presented in table II-4, and the variation by time of water discharge, sediment concentration and sediment discharge are presented in figures bellow (II.7, II.8, II.9).

Table II-4 The statistical parameters of the applied data set

Data set	Data type	Mean	Std	Min	Max
Training Set	WD (m^3/s)	22.20	47.84	0.005	800
	SSD (Kg/s)	280.73	1525	0.00056	23250
Validation Set	WD (m^3/s)	8.08	26.00	0.0262	575.20
	SSD (Kg/s)	320.98	1775.3	0.004	20681
Testing Set	WD(m^3/s)	4.90	16.97	0.010	359.10
	SSD (Kg/s)	124.01	992.75	0.002	15600

WD: Water discharge, SSD: Suspended Sediment Discharge.

II.2.11 The Lakhdaria hydrometric station:

The Lakhdaria station controls the Isser Wadi that runs through the north western part of the wilaya of Bouira and drains a watershed of 4140.9 km². Its location is in connection to the Beni Amrane upstream, about 10 km northwest of the city of Lakhdaria. The station is founded in 1954, operated until April 1958. In December 1965 it was called into operation, with the level of water increased. The quality and accuracy of measurements seem reasonable.

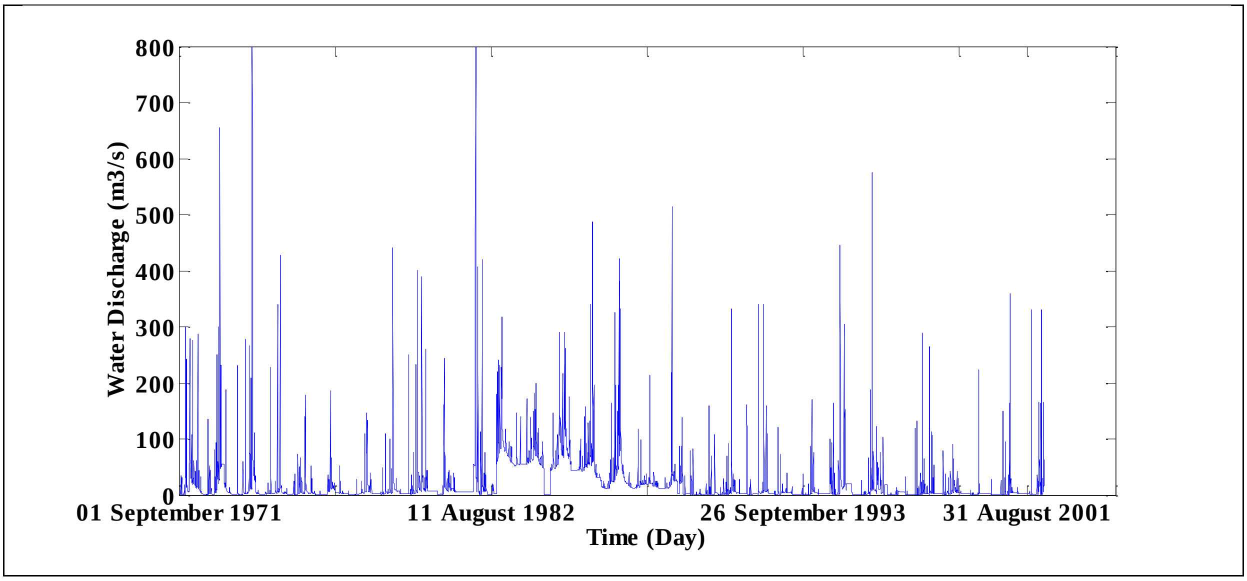


Figure II.7 Time series of the used water discharge data.

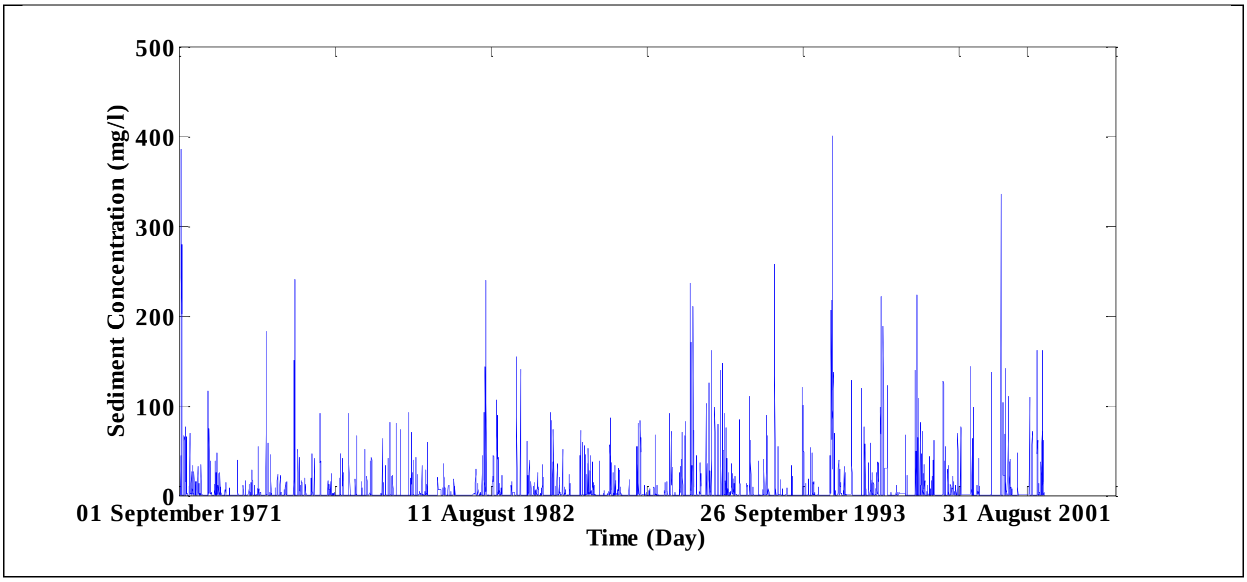


Figure II.8 Time series of the used sediment concentrated data.

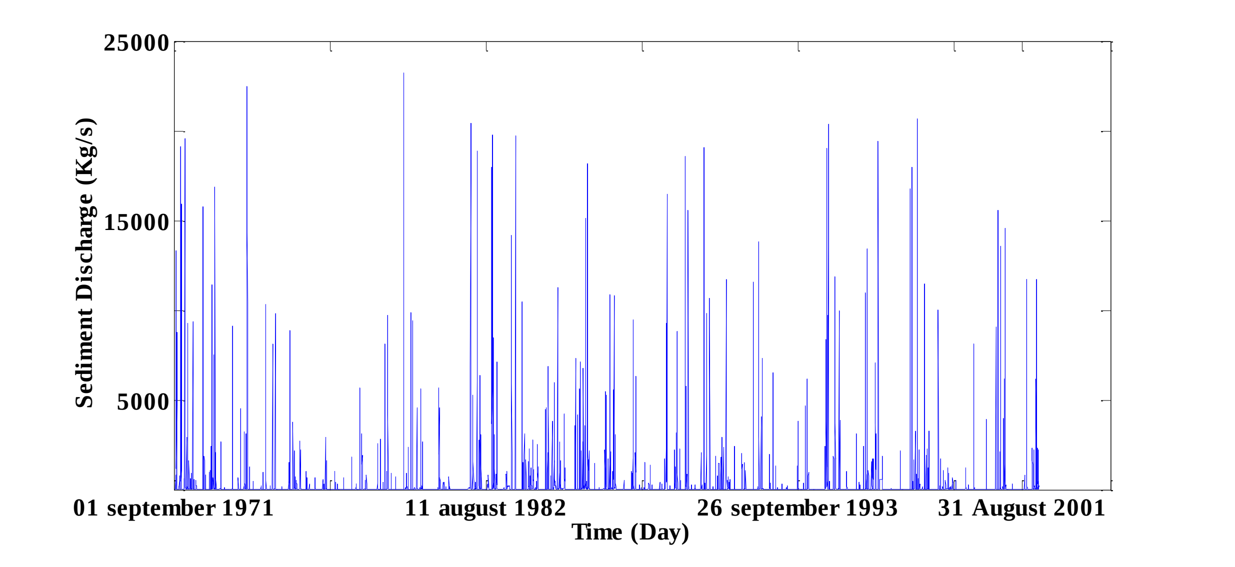


Figure II.9 Time series of the used sediment discharge data.

II.2.12 The urban hydro-system construction:

The Beni Amrane's reservoir has very important strategy in the north central part of Algeria. It is used as a buffer zone to transfer the water from the Isser Wadi to the Keddara's dam, which supplies the city of Algiers and part of Boumerdes in drinking water. The supply by the Isser Wadi to the city of Algiers is 114 hm3/yr Taouche, (2007). On the 2006 the national agency of dams and transfers stated that the transfert of water from the Beni Amrane reservoir to the city of Algiers was 86 Hm3.

The hydro systems construction between the Beni Amrane reservoir to the Keddara reservoir and the city of Algiers is based on the following hydraulic constructions information taken from the engineering thesis of Taouche, (2007):

- A dam with an impoundment level of 39.5 m from the riverbed, with water retaining capacity of 15.6 Mm^3.
- An intake structure and pumping station with a capacity of 7 m^3/s in the Isser Wadi.
- A linking water pipe between the Beni Amrane reservoir to the Keddara's retain with a diameter of 2 m and distance of 31.3 km.
- A linking water pipe with 5.65 km length, and 2 m diameter between the keddara dam and the water treatment station. Two paired linking pipes

between the water treatment station and the city of Boudouaou with a distance of 3.1 km and diameter of 1.5m.

- The average water discharge in the water treatment station is 6.25 m^3/s in the city of Boudouaou.
- Two linking pipes with of 1.5 m diameter from Boudouaou to Algiers with a couple of connections to the feed tanks of the cities of Gue de Constantine, El Harache and Beaulieu.
- Different feed tanks and pumping stations in Gue de Constantine, Beaulieu and Sidi Garidi, with a distance of the water pipes of 104 km around Algiers.

II.3 THE GREAT KABYLE WATERSHED

II.3.1 The geographical situation:

The Great Kabyle watershed is a sub-basin in the Algiers Coastal Basin, it is located at 37°00′N~36°25′N and 4°45′E~ 3°45′E, north central Algeria, on the eastern side of the Isser watershed, It is total area is 2600 km².

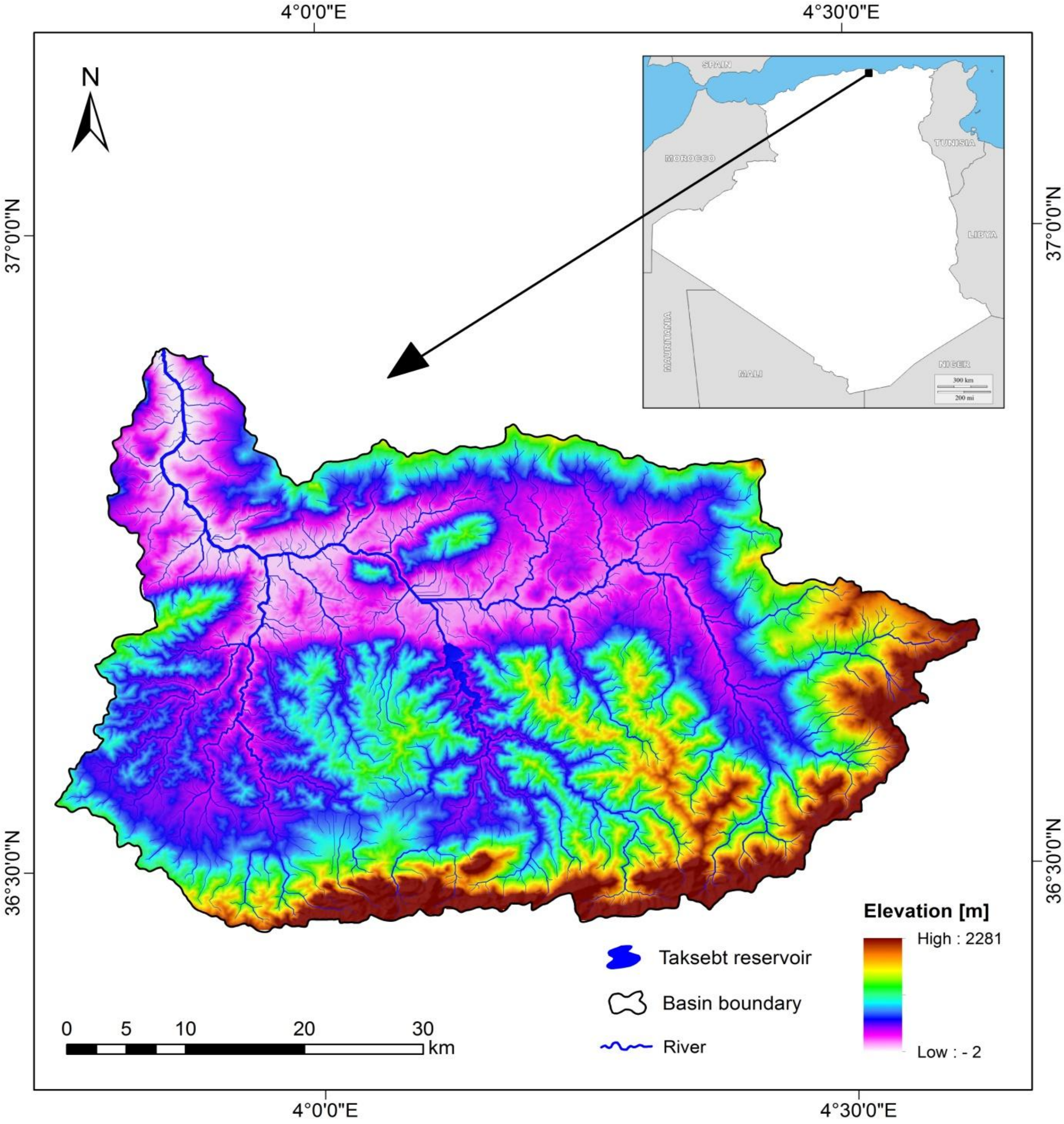


Figure II.10 The geographical map of the Great Kabyle watershed.

II.3.2 The altitudes:

The watershed is located in the north of the Tellien Atlas which is entirely mountainous. The highest point is located in Djbel Djurdjura with an altitude of 2301 m (Lalla Khedidja) which is the highest point in Algeria. The lowest point is 0 m which is in the valley's outlet. The average altitude of the Great Kabyl watershed is around 635 m.

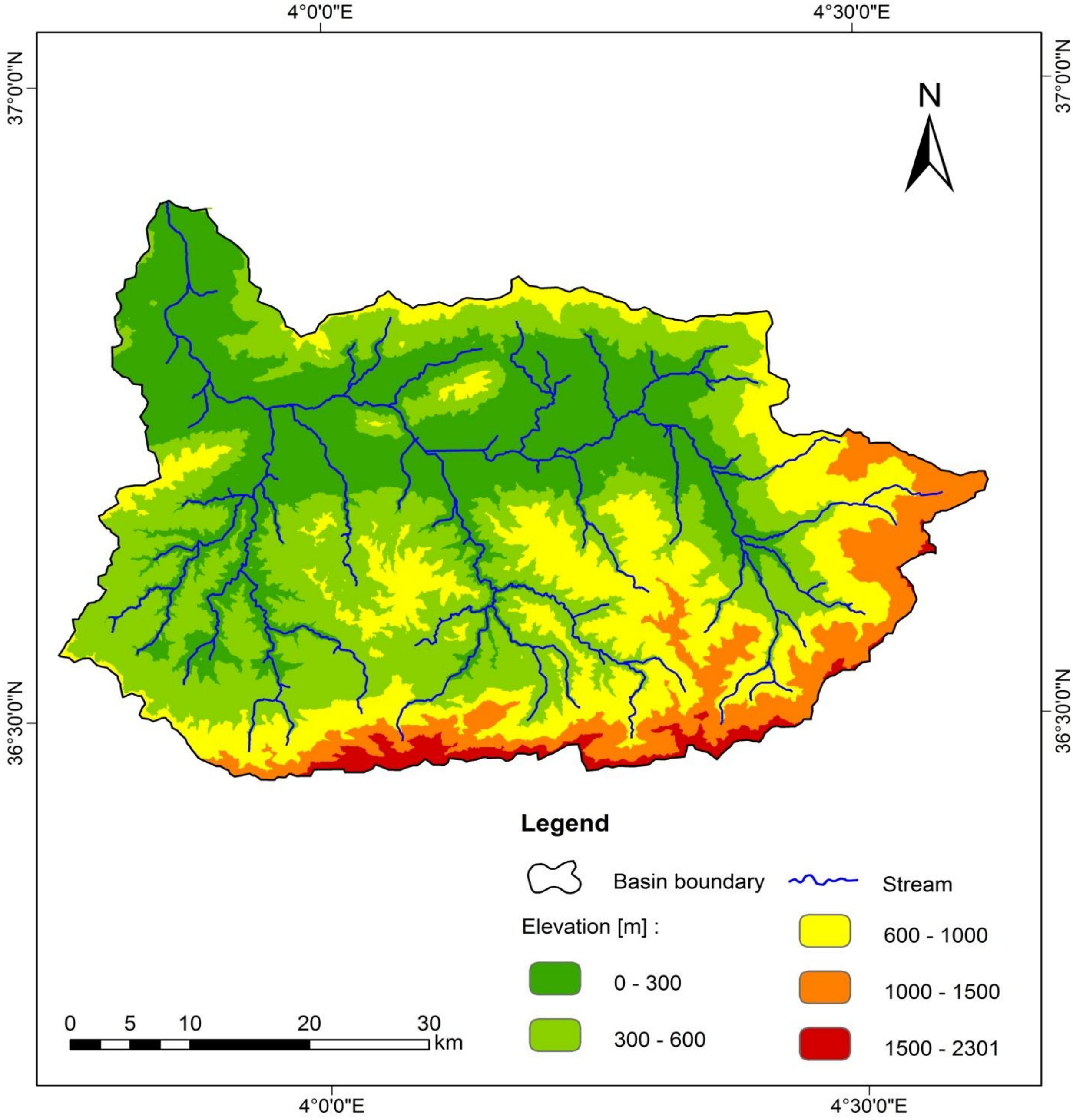


Figure II.11 the elevation map of the Great Kabyle watershed.

II.3.3 The relief:

The basin is characterized by roughly steep slopes; according to table II-5, around 11% (288 km²) of the watershed area consists of slopes less than 7%, more than 70% of the area (235 Km²) consists of slopes varying between 10% and 35%. While the lands with slopes greater than 35% represents around 536 Km² with 21% from the total area of the Great Kabyle watershed, and around 20% of the watershed area with 536 Km² presenting slopes greater than 35% located mostly in the southern part of the watershed in the Tellin Atlas.

Table II-5 The distribution of surfaces based on the elevation.

SLOPES [%]	AREA [m²]	AREA [%]
< 3	117,86	4.71
3 - 7	170,21	6.80
7 - 12	335,10	13.39
12 - 20	610,73	24.41
20 - 35	731,66	29.25
> 35	536,21	21.43

The following figure II.12 explaines the distribution of surfaces on the Great Kabyle watershed based on the slopes, and we can notice from the figure that the high slopes are figured out in Tellien Atlas in the north of the watershed.

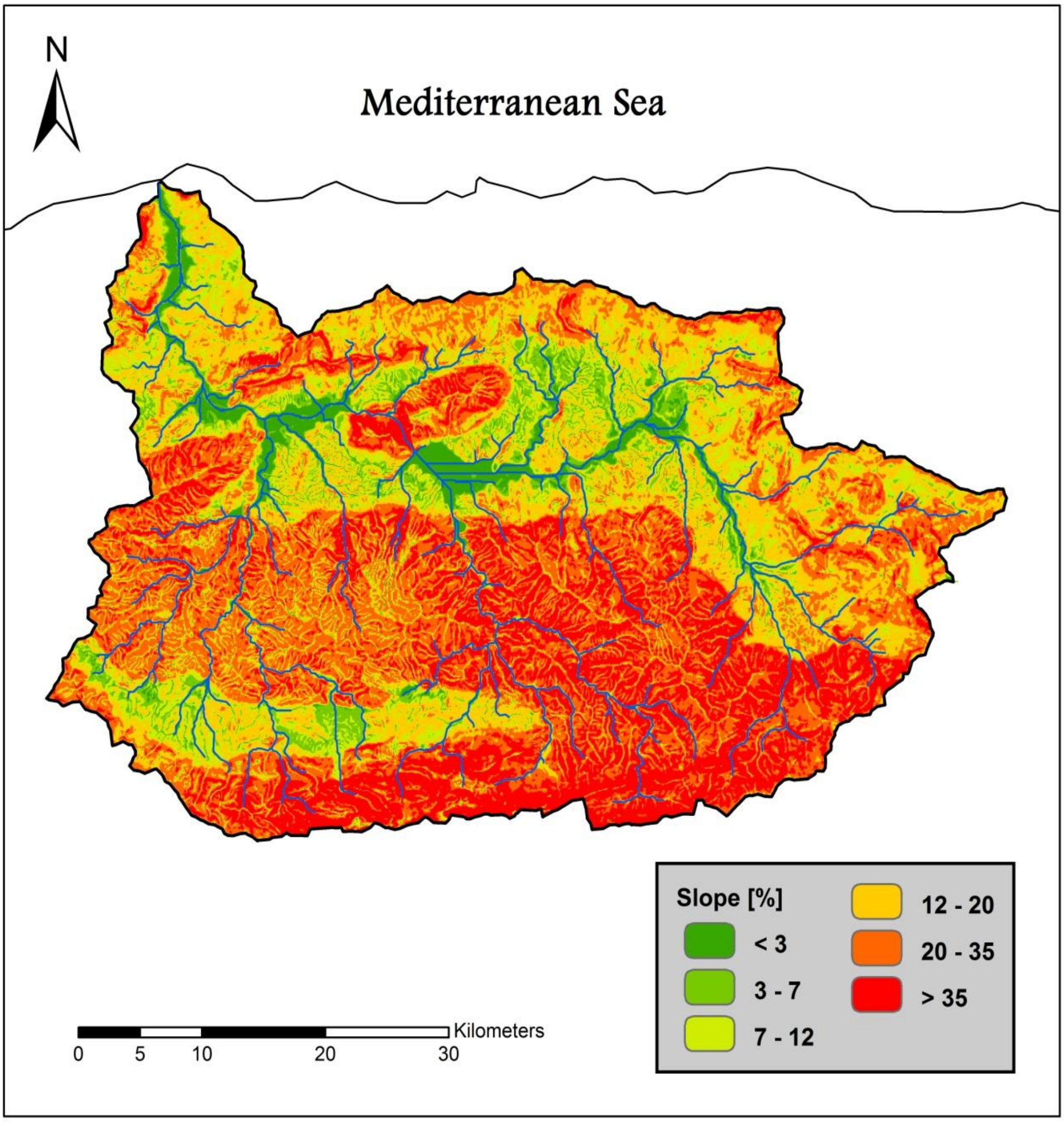


Figure II.12 The Slope map of the Great Kabyle watershed.

II.3.4 Hydrology

The basin is dominated by a Mediterranean climate with a humid southern part and a sub-humid northern part. The mean annual precipitation is at about 850mm/yr while the temperature averages 18.1°C per year. The Great Kabyle watershed is characterized by a dense and well-branched river system. The table bellow (Table II-2) presents the hydrological characteristics of the Great Kabyle watershed.

Table II-6 The hydrological characteristics of the Sebaou watershed.

CHARACTERISTICS	VALUES
Area (Km²)	2500
Perimeter (Km)	265
Max Elevation (m)	2301
Min Elevation (m)	0
Average Elevation (m)	635
Order	08
The sum of Thalwegs in watersheds (Km)	6211
The number of perennial streams	5751
Drainage density (Km/Km²)	2.48
The stream's order of the main stem	2.29
The factor of the torrential nature of rainfall	5.69
Average Rainfall (mm)	850

ΣLi, the sum of thalwegs in the watershed; ΣN1, the number of perennial streams; Dd, drainage density; F1, the stream's order of the main stem; Ct, the factor of the torrential nature of rainfall.

II.3.5 The water system:

As over mentioned the Sebaou Wadi is characterized by a very dense and well branched river system, the southern boundary of the river is formed mainly by the mountain range the Tellien Atlas. The study was conducted on the north part of the Sebaou Wadi which is Located on the east of the capital of Great Kabyl watershed (Tizi Ouzou). The Great Kabyle watershed is divided into 9 sub-watersheds. The Sebaou Wadi is separated by three main hydrometric station; the Azazga hydrometric station which controls the lower part of the Wadi, the Belloua hydrometric station which is located in the middle of the Sebaou Wadi geographically, and hydrographically is controlling the medium Great Kabyle watershed and Sebaou Wadi, and it is located in the amount of the Taksebt's dam (Figure II.15) covering a surface of 1490 km². The last main hydrometric station is the Baghlia hydrometric station which gauges the upper Sebaou which is known as the maritime Sebaou.

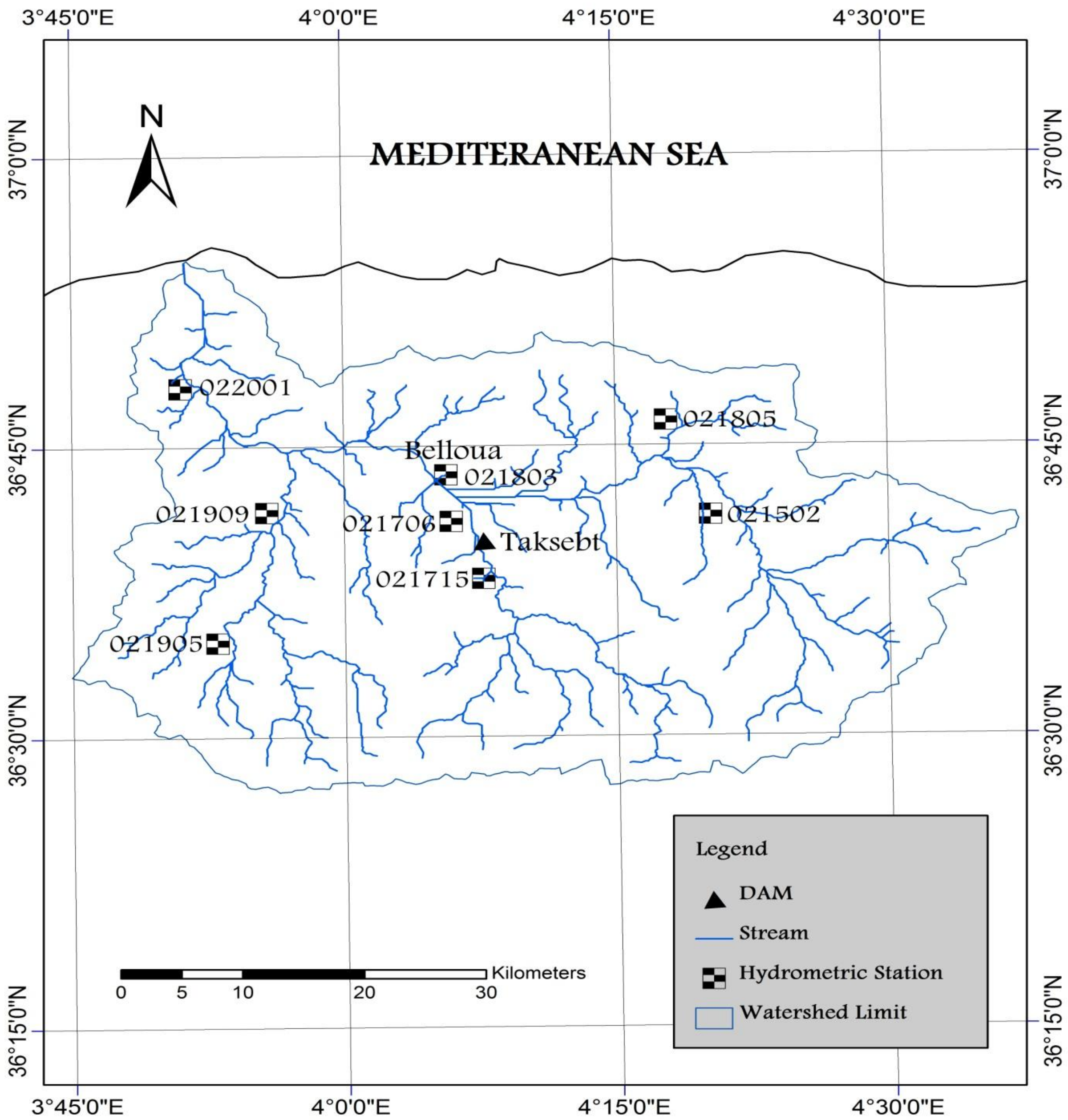


Figure II.13 Map of the Sebaou Wadi and Belloua hydrometric station.

II.3.6 Geology and morphology of the Great Kabyle watershed:

On the figure II-13 bellow, it is clearly noticed on the soil map that the unsaturated soil is dominating the watershed area, especially on the southern part of the watershed. It is also noticed from the map that the area around the Sebaou Wadi in the watershed it is mainly formed by the calcareous soil, and the Wadi way is formed by alluvial soil as it is showed in the map bellow. The eastern side of the watershed it is formed by the podzolic soil. The figure II-13 illustrates well the structure of soil in the watershed.

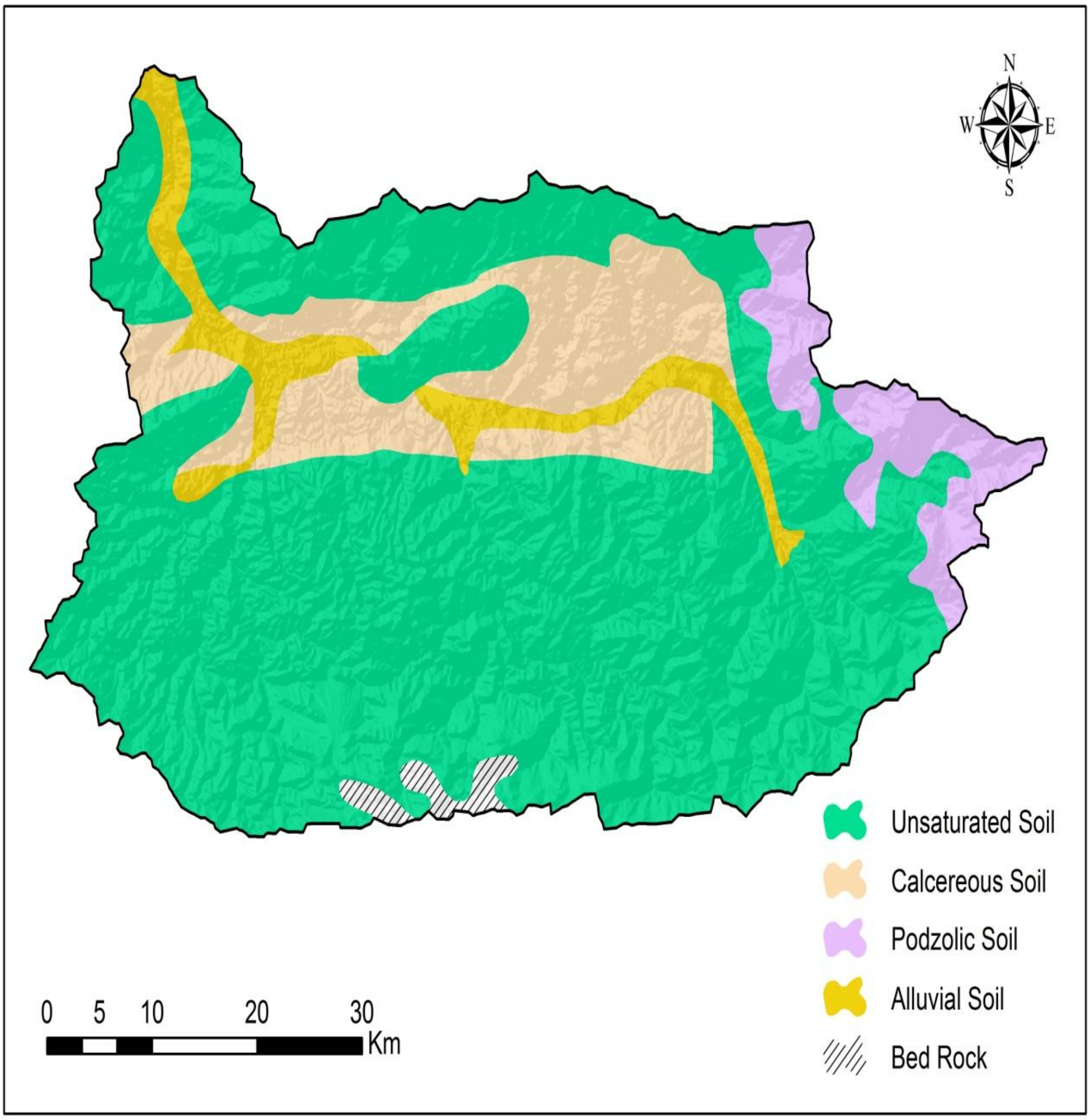


Figure II.14 Soil map of the great kabyle watershed.

II.3.7 The vegetal cover of the Great Kabyle watershed:

The vegetation cover is very dense in the Great Kabyle watershed, according to the map of the Landsat8 (Figure II.14) the vegetation cover is fairly high from the north and east, and the density decreases heading to the west. According to the study of Ammari A, H, (2012) in the lower altitudes the dominant vegetations comes from olive trees. On the upper altitudes in the Djurdjra mountainous chain, the dominant trees are the oak and cedar.

The land cover map in the figure below shows high vegetation density in the Great Kabyle especially on fairly high maquis, the density decreases by heading west. Ammari A, H, (2012) states that in this area the vegetation density follows exactly the rainfall intensity, with a high vegetal cover density in the areas where the rainfall registers more than 850 mm per year. The figure II.14 bellow is based on the Landsat 8 images that were taken on the 7th May 2014. The map shows that the Great Kabyle watershed is considered as very dense area by the vegetal cover.

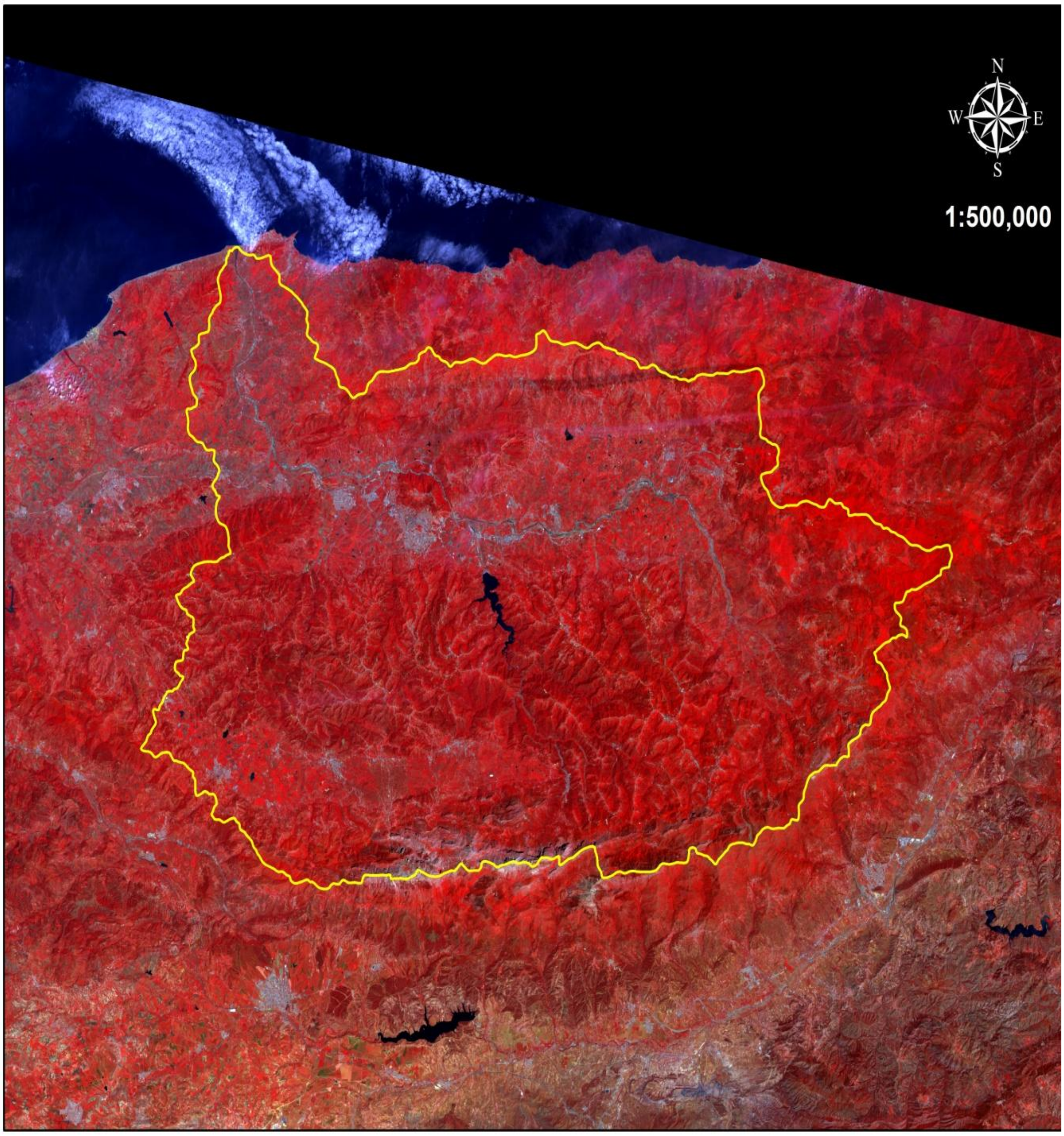


Figure II.15 The vegetation cover image of Landsat8, bans combination 5, 4, and 2. Dated: 2014-05-07T17:24:31.

II.3.8 The Taksebt reservoir:

The construction of the Taksebt's dam started in 1994 and ended in 2000, it is situated in the wilaya of Tizi Ouzou on the Beni-Aissi Township. It is an earth-fill dam of 94 m high and 515 m long. According to National Agency of Dams and transfers, the Taksebt dam supplies the city of Tizi Ouzou and part of Algiers in drinking water. Therefore, on one hand the water quality in the Taksebt dam must be adequate to be supplied to the cities, and on the other hand the water resources of this watershed that is showing very high vegetation density, which is very important for the agricultural side.

Table II-7 The principle characteristics of the Taksebt dam.

CHARACTERISTICS OF THE DAM	VALUES
The altitude of the river bed from the base of the dam	94.00 m
The altitude of the spillway crests	165.00m
The altitude of the dam crest.	169.62m
the length of the dam	515 m
Initial capacity	175.00 Hm3
The last registered capacity (2004)	181.02 Hm3
The average annual rapport	196.00 Hm3
The average annual silting	0.27 Hm3
The watershed surface	1560 km^2
The average annual rainfall	850mm

In the Sebaou Wadi there is only the Taksebt reservoir, and according to the study of Ammari Abdel Hadi, (2012) and the National Agency of Reservoirs and Transfers (l'Agence Nationale des Barrages et Transfers) the capacity of the Taksebt dam represents only 16% of the average annual rapport of the Sebaou Wadi.

II.3.9 The data base of the Sebaou Wadi:

The watershed of the Great Kabyle has total area of 2600 km^2. It is divided into 9 sub watersheds, managed and controlled by 9 hydrometric stations from the Algerian national agency of hydraulic resources (ANRH): Baghlia (022001), RN30 (021715), Belloua (021803), Freha (021805), Azazga (021502), Draa Elkifen (021905), (Missed nomination; 021909), (Missed nomination; 021905).

II.3.10 The statistical data parameters:

To model the relationship between water discharge and sediment discharge in the watershed of the Sebaou Wadi, a data set consisting of several parameters was used. The study was carried out on daily sediment discharge and water discharge data of 9 years between 1st September 1978 and 31st August 1987. The data sets were divided into three sets: training, validation and testing. The validation set was used only for cross validation. The data series used in this study was from the National Agency of the Hydraulic Resources (ANRH). The used data come from the Belloua hydrometric station under nomination (021803). The table bellow (Table II-8) shows the statistical parameters of the Belloua Hydrometric station during the used period in this study.

Table II-8 The statistical parameters of applied data set

Data set	Data type	Mean	Std	Min	Max
Training Set	WD (m^3/s)	311.86	857.36	0.11	14972
	SSD (Kg/s)	40.47	423.99	0.002	14972
Validation Set	WD (m^3/s)	231.81	816.37	26.88	12883
	SSD (Kg/s)	48.65	595.55	0.47	10376
Testing Set	WD(m^3/s)	335.79	676.26	31.18	7024
	SSD (Kg/s)	41.36	220.36	0.34	2801

WD: Water Discharge, SSD: Suspended Sediment Discharge

II.3.11 The Belloua hydrometric station:

The Belloua hydrometric station controls the upper area of the Sebaou Wadi that runs through the east of the wilaya of Tizi Ouzou and drains a couple of sub watersheds in the Great Kabyle watershed with approximate surface of 1432 km^2. The Belloua hydrometric station is located between the downstream of Taksebt dam and the city of Tizi Ouzou.

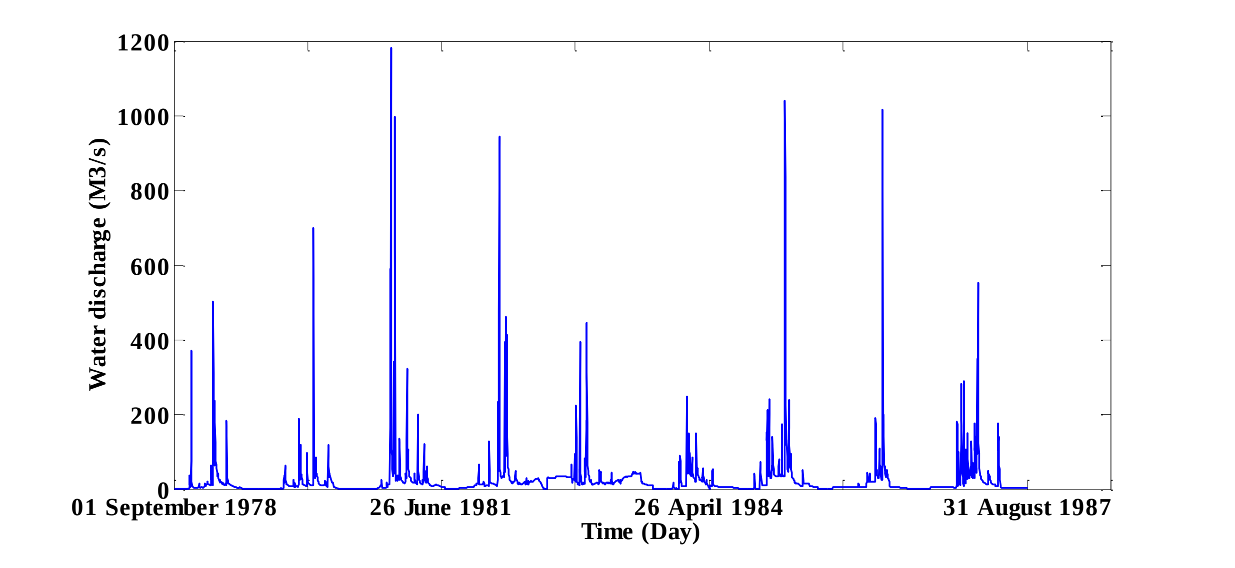


Figure II.16 Time series of the used water discharge data.

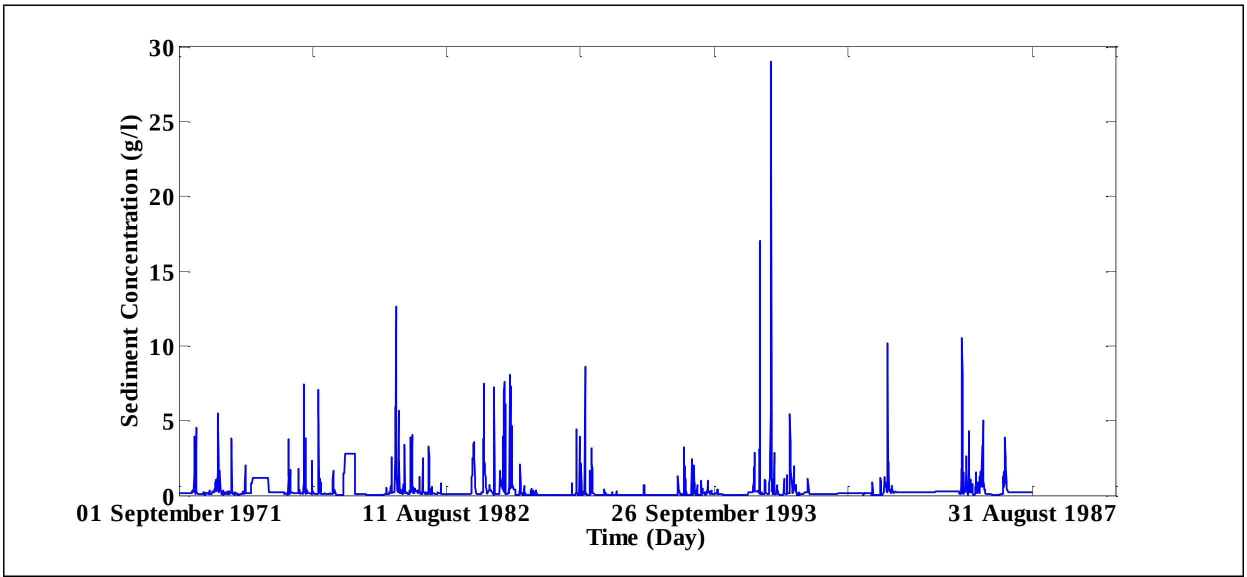


Figure II.17 Time series of the used sediment concentrated data.

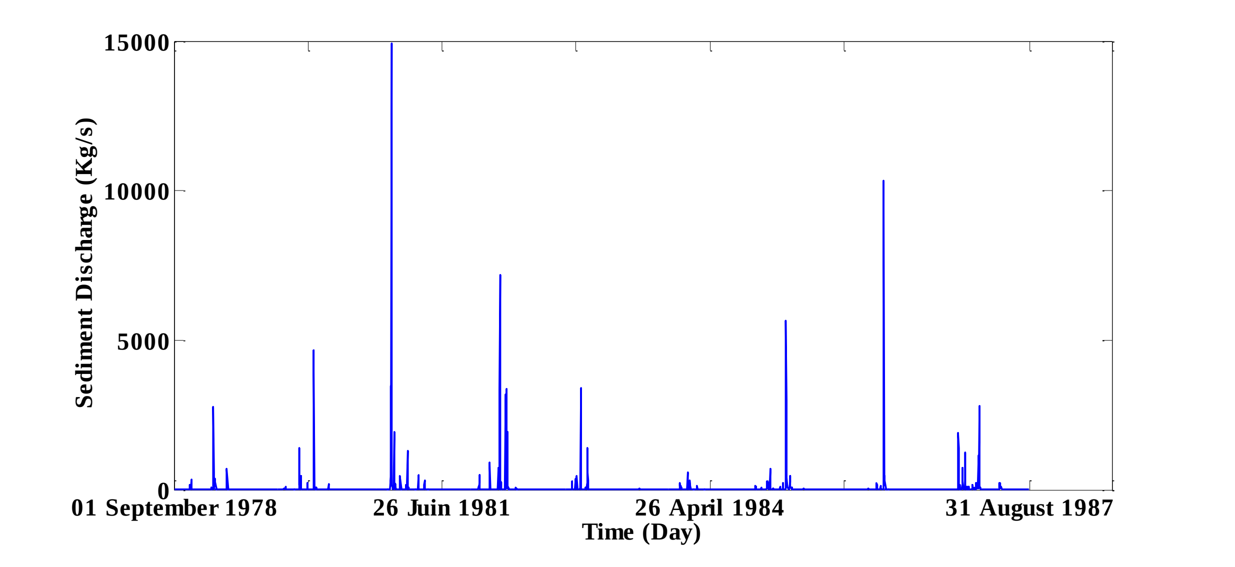


Figure II.18 Time series of the used sediment discharge data.

III. ARTIFICIAL NEURAL NETWORKS

III.1 OVERVIEW:

Artificial Neural Network (ANN) is one of the mathematical models for forecasting by using pattern matching and comparison procedures Fischer, (1998). NN are one approach within the broader hydro-informatics framework which emerged in the 1990s as a route to managing information overload in an effective way Govindaraju, (2000).

ANN is one of the most significant strengths of the Artificial Intelligence (AI) techniques that hydrologists used in the last twenty years, which helped researchers to handle all data types, and predict different nonlinear phenomena. The purpose of this chapter is to introduce and illustrate the basic terms of the neural networks modeling. The most used Neuro-Hydrological tools and models are introduced in this chapter.

III.2 THE STRUCTURE OF ANN:

The ANN structures are based on the biological neuronal networks. The figure III.1 bellow presents the ANN structure. In every single element called neurons, nodes or units, there is an information processing. The connection link between neurons are transmitted by signal, every connection link has an associated weight (w) that represents its connection strength.

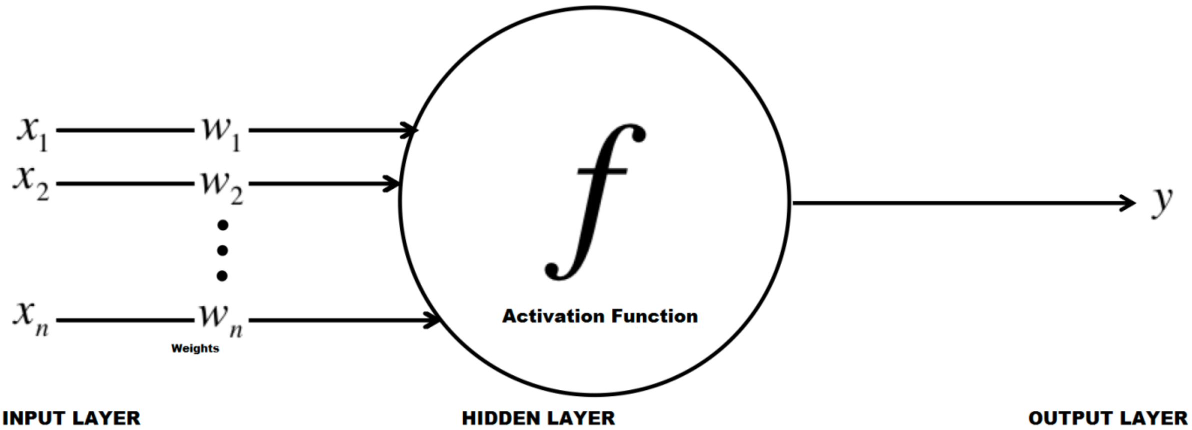


Figure III.1 The structure of Neural Networks.

III.3 TRAINING AN ANN:

III.3.1 Introduction

There are four different learning methods that can be used in ANN, supervised learning, reinforcement learning, stochastic learning and unsupervised learning. In this section of the chapter we present two basic comparative learning methods are mostly used in ANN; supervised and unsupervised learning.

III.3.2 Supervised learning:

Training data sample based on supervised learning takes from data source with assigned correct classification. The use of these techniques are usually utilized by the feed forward or multilayer perceptron models. Sathya and Abraham, (2013) stated 3 distinctive characteristics for Multi Layered Perceptron (MLP) based on supervised learning:

- One or more layers of hidden neurons that are not part of the input or output layers of the network that enable the network to learn and solve any complex problems.
- The nonlinearity reflected in the neuronal activity is differentiable.
- The interconnection model of the network exhibits a high degree of connectivity.

The supervised learning is based on two different methods; one called Error Correction Learning Rule and second called Memory Based Learning Rule.

III.3.3 Unsupervised learning:

To identify the hidden patterns in unlabelled input data for self organizing neural networks is based on unsupervised learning algorithm. The role of unsupervised learning is to learn and organize input information without evaluating the potential solution (Kohene et al., 1996).

Sathya and Abraham, (2013) stated the main characteristics for the Self Organizing Maps;

- It transforms an incoming signal pattern of arbitrary dimension into one or 2 dimensional map and perform this transformation adaptively.

- The network represents feed forward structure with a single computational layer consisting of neurons arranged in rows and columns.
- At each stage of representation, each input signal is kept in its proper context.
- Neurons dealing with closely related pieces of information are close together and they communicate through synaptic connections.

The unsupervised learning is based on two different methods of learning; one based on Competitive Learning Rule and second called Hebbian Learning Rule. The unsupervised learning is also called as competitive layer Sathya and Abrahart, (2013).

III.4 MAIN CATEGORIES OF ANN MODELS

III.4.1 Feed Forward Back Propagation Neural Network (FFBPNN):

The most popular 'default' training algorithm is back propagation Rumelhart et al., *(*1986), Tveter, (2003) and Abrahart et al., (2004). It is widely used to solve complicated nonlinear functions. It is supervised learning algorithm used for training artificial neural network. This technique offers an efficient computational procedure for evaluating the derivatives of the network performance function. The Back Propagation Neural Network is widely used as a multi layer learning network, consisting of an input layer, hidden layers (one or more hidden layers depending on the network structure) and output layer. Adjustable weights are used to connect the nodes between adjacent layers and optimized by training algorithm to get the desired classification results C.Lin, (2007). Figure III.2 illustrates the configuration of BP network.

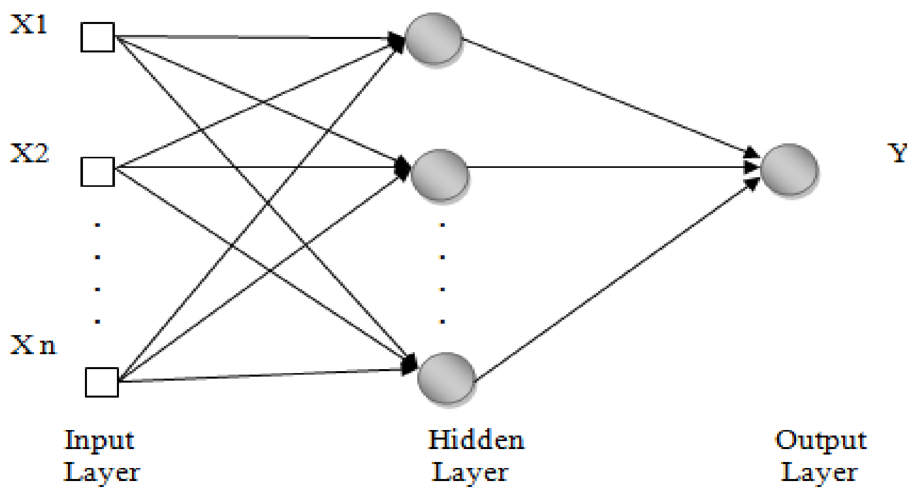


Figure III.2 Structure of BP neural network Selected

III.4.2 Focused Time Delay Neural Network (FTDNN):

FTDNN is one of the most straight forward dynamic networks. The basic architecture is the same for all the models. FTDNN consists of a Feed Forward Network with a tapped delay line at the input (shown in Figure III.3). It is an element of dynamic networks family, which is called focused time delay networks, in which the dynamics appear only at the input layer of a static multi-layer feed forward network, which makes it suitable for time series prediction Htike and Khalifa, (2010).

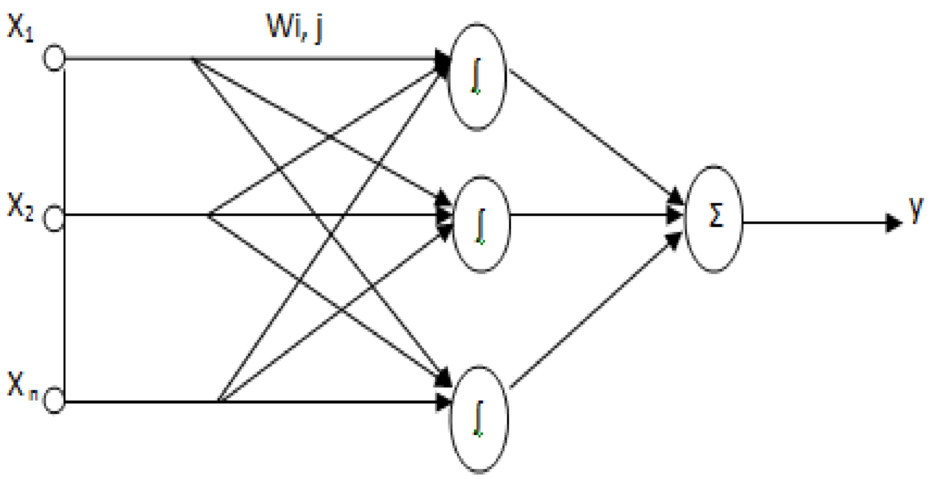


Figure III.3 The Focused Time Delay structure.

III.4.3 Radial Basis Function Neural Network (RBFNN):

Radial Basis Function networks have been proposed and used in many studies, for examples: Renals and Rohwer, (1989), Fernando and Jayawardena, (1998), Leonard et al., (1992). Radial Basis Function (RBF) is considered the second most popular model after Back Propagation (BP). The RBF network consists of three layers: input, hidden, and output. The main architectural differences between an RBFNN and a standard BPNN is that in the former, the connections between the input units and the hidden units are not weighted and the transfer functions in the hidden units possess radial-symmetric properties (as opposed to sigmoidal). The hidden units perform a fixed non-linear transformation with no adjustable parameters and the output layer combine these results in a linear fashion, in most cases, using a simple summation Leonard et al., (1992) and Abrahart et al., (2004).

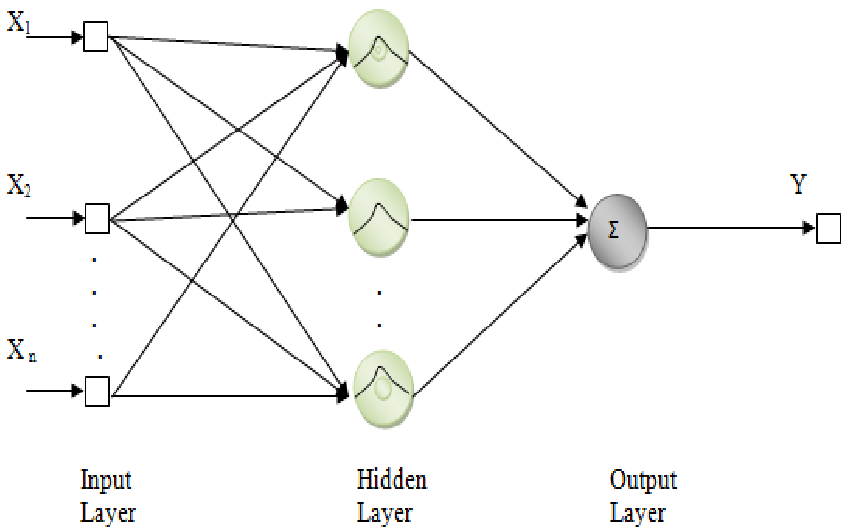


Figure III.4 Structures of radial basis function selected

III.4.4 Cascade Correlation Neural Network (CCNN):

Cascade Correlation Networks is a supervised learning algorithm in artificial neural network. The CCNN begins with only input and output neurons. During the training process, instead of just adjusting the weights in a network, CC starts with the minimal network, then neurones are selected and added to the hidden units one by one selecting multi layer structure Fahlman and Lebiere, (1990). Each input is linked to each output neuron by receiving adjustable weighted sum from all input neurones including the bias. The final output is produced by the output neurones using different transfer functions Adhikari A et al., (2013).

III.4.5 Recurrent Neural Network (RNN):

Kumar et al, 2004 states that the antecedent values in forecasting hydrologic time series is depending on the number of the persistence components. The RNN provides additional feed-back links to the feed-forward connections Sajikumar and Thandaverswara, (1999). The input can be sent by the generalized recurrent neural network in either direction from and to all the layers. The output of the networks depends on the external inputs that it receives and the previous time step at the same time. The RNN can deal with complicated phenomenon that are based on events from the past and use it in current computations Kumar, N et al., (2004).

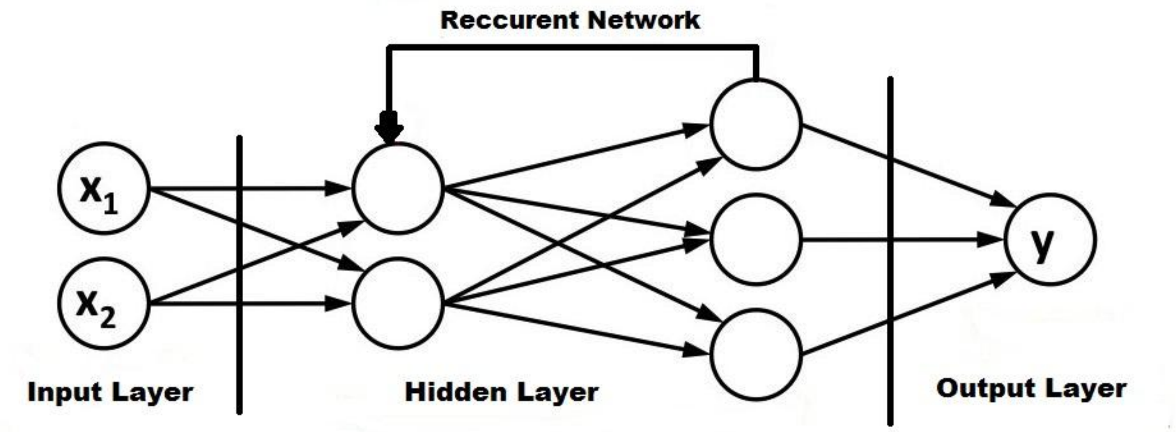


Figure III.5 Structure of the Recurrent Neural Network

III.5 OVERFITTING IN ANN:

III.5.1 Overview:

When training a neural network, the learning process is continued until obtaining a network with optimal generalization performance. However, the over-fitting can be detected in most of neural network models based on MLP architectures. While the training network seems to get better and the average error of the training set is decreasing, at some point the error of the unseen examples increases. In other words the error of the validation set at some point start increasing Khadir, (2005); Orr and Muller, (1998); Prechlet, (1998).

In the last twenty years a number of techniques have been developed to avoid over-fitting that occurs during neural network training. Among the techniques that were applied were Weight Decay and Noise Injection (Zur et al., 2009; Piotrowski and Napiorkowski, 2013), Optimized Approximated Algorithm (Yinyin Liu et al., 2008) and Early Stopping (Prechlet, 1998; Khadir, 2005; Zur et al., 2009; Piotrowski et al., 2014; Tachi et al., 2016).

It is important to make sure that the network does not become over-familiarised with the training data, because this causes the network to lose its power to generalise to the unseen data sets. The data set used in this process may be referred to as a 'validation' set.

If a neural solution has insufficient complexities, or has been under-fitted, it will fail to detect the full signal in a complicated data set. If the neural solution is too complex, or has been over-trained, it will robust the noise as well as the signal. A difficult and continuous assessment would be required to distinguish between these contrasting situations in an effective way throughout the different stages of construction and development. Different techniques are required to avoid over-fitting that occurs in neural networks (Abrahart et al., 2004, chapter 2).

III.5.2 Techniques to avoid over-fitting:

III.5.2.1 Noise Injection (jitter):

The method of noise injection refers to adding an artificial noise to the input data during training process. With this method, a noise vector is added to each training case in between training iteration (Zur et al., 2009). The added jitter will produce a smoother final mapping between inputs and outputs Abrahart and White, (2000).

III.5.2.2 Weight Decay:

The Weight Decay is a modified error function E(w)=E(w)+alfa W, where E(w) is the cross entropy error function and alfa is a parameter that control the penalises Artificial Neural Network weights against large values, in order to create a smoother final mapping between inputs and outputs Zur et al., (2009).

III.5.2.3 Early Stopping:

The Early Stopping criterion is based on cross validation technique. The validation set is necessary to define stopping criteria of the optimization algorithm Piotroswki and Napiorwski, (2013). The validation set is introduced to the error during training process, knowing that only training data was used during training set. The network minimize the error during training set while its probably decreasing during validation set on some points. The Early Stopping criterion terminates the ANN learning when the calculated error increases for validation data. The error of the validation data may still go further down after it has begun to increase, however it is not easy to decide when exactly to stop training Sjoberg and Ljung 1992; Ammari et al 1996; Prechlet 1998; Orr and Müller, 1998; Khadir, 2005; Piotrowski et al 2014 and Tachi et al., 2016.

III.5.2.4 Optimized Approximated Algorithm:

The Optimized Approximated Algorithm (OAA) is recently proposed method by (Yinyin Liu et al., 2008) for optimizing the number of the hidden neurons in MLP's back propagation training sets. The OAA avoids over-fitting by stopping criteria based on the estimation of the signal –to –noise –ratio –figure (SNFR). The SNFR detects automatically the over-fitting by checking the goodness of fit from only the training set Yinyin et al., (2008).

III.6 ADVANTAGES AND DISADVANTAGES OF ANN:

Different advantages and disadvantages faced the researchers using Artificial Neural Network to predict different problems and phenomenon. Some of this advantages and disadvantages were stated by Khadir, (2005) in unpublished document giving a general overview of ANN.

III.6.1 Advantages of ANN:

- Tolerance to high uncertainly.
- Easy for application and does not require a thorough understanding.
- The large choice of network models, its types, architectures and various activation functions.

- The non linearity of ANN models which helps the most hydrological problems because of their non linearity.
- The powerful potential of ANN models to solve the hard computational problems.
- The ability to model input/output relationships on the non understood problems, that they do not have an explicit mathematical equation between input and output.

III.6.2 Disadvantage of ANN:

- The black box nature of ANN is the main disadvantage, which is hard task to find the physical meaning.
- Despite a solid theoretical foundation, the choice of network often falls to the user because it does not exist for any use proven guide.
- The nonlinear nature of ANN's can trap the user to over-train the network.
- Hard to justify the network type and architecture that used in most of models.

III.7 MODEL PERFORMANCE EVALUATION

For evaluating the performance of the models we used two different equations to calculate the error between observed and estimated data.

III.7.1 Coefficient of determination (R^2)

Coefficient of determination (R^2) describes the degree of co-linearity between simulated and measured data; R^2 describes the proportion of the variance in measured data explained by the model MORIASI *et al*. (2006). R^2 ranges from 0 to 100%, with higher values indicating less error variance, and values greater than 50% considered acceptable [SANTHI *et al*. 2001; VAN LIEW *et al*. 2003]. The coefficient of determination R^2 has been used for further analysis to evaluate the performance of the predictive model. It is defined as follows:

$$R^2 = \left(1 - \frac{S_{cr}}{S_{ct}}\right) 100 \qquad (1)$$

S_{cr} = square sum of residues.

S_{ct} = square sum of total.

III.7.2 Index of agreements (RMSE)

Several error indices are commonly used in model evaluation, including Root Mean Square Error (*RMSE*). These indices are valuable because they indicate error in the units (or squared units) of the constituent of interest, which aids in analysis of the results. *RMSE* values of 0 indicate a perfect fit SINGH & WOOLHISER, (2002). The root mean square error was used to test the statistical significant between estimated and observed suspend sediment concentration which can be expressed as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left[(\dot{\theta} - \theta)^2 \right] \qquad (2)$$

$$RMSE = \sqrt{MSE} \qquad (3)$$

Where θ is the observed sediment discharge, $\dot{\theta}$ is the predicted sediment discharge and n is the number of observation.

III.8 USE OF ANN IN HYDROLOGY:

III.8.1 Overview:

This section examines the use of artificial neural network in hydrology. It is confirmed that ANNs are robust tools for modelling many nonlinear hydrologic processes such as rainfall-runoff, ground water management, water discharge-sediment discharge, flood and precipitation ASCE, (2000b).

III.8.2 Modelling rainfall-runoff using ANN:

The nonlinearity and the complexity of the relationship between rainfall-runoff is one of the most important problems in hydrology. Many factors and different hydrological parameters such as sediment load, land use, evaporation, infiltration, watershed geomorphology etc, are depending on runoff.

In the middle of 90's number of hydrologists have started applying ANN models in modelling watershed runoff depending on rainfall inputs. One of the earliest research paper in modelling rainfall-runoff was carried out by Halff et al., (1993), where they used a three layer feed forward ANN approach for prediction of watershed runoff at bellvue, washinton. The authors used five rainfall storm events (four storm events for training and one for testing). This study research opened the way for other researchers for watershed runoff prediction using ANN models. We mention couple of these researches that were obtaining during last 25 years; (Minns A.W and Hall M.J., 1996; Savic et al., 1999; Jain et al., 2001; Tokar and Johnson, 1999; Solomatine and Dulal, 2003; Kissi, 2004, Wang et al., 2009, Tayeb et al. 2016 From our research investigation we can say that most ANNs application in hydrology (in hydrological journals) are discussing the prediction of flow depending mostly on rainfall and some other climatic parameters.

III.8.3 Modelling Stream Flow using ANN:

Depending on the research studies that they were made by ASCE, (2000b) and Maier et al., (2010) were they explained the application on ANNs in hydrology. The estimation of stream flows without depending on precipitation as input was the focus of some papers. One of the first researches in prediction of stream flow were carried out by Kang et al., (1993) where he compared ANN with autoregressive models to predict on daily and hourly scale. Another two studies were obtained by Karunanithi et al., (1994) and Muttiah et al., (1997) who used the cascade correlation algorithm for streamflow and peak discharge in watersheds. Kamp and Savenije, (2007) predicted streamflow and other different parameters. The ANN models in predicting streamflow achieved the stream flow prediction and showed effective and reliable forecasts in different papers that dealt with this phenomena. It has shown better performances values comparing to the regression models ASCE, (2000b).

III.8.4 Modelling sediment load using ANN:

The non linearity and complexity of the suspended sediment and its estimation led hydrologists for many decades to use different statistical models and equations to forecast and estimate this phenomenon. Because of the complexity and different factors affect in the sediment load in river, watershed and reservoir, it was hard to get a satisfying predictive model by the classical models.

In the middle of 90's hydrologists started applying Artificial Neural Network techniques to estimate runoff depending on rainfall and different climatic parameters. In 2000 the use of artificial neural network extended to the estimation of suspended sediment discharge, the first applications of ANN in this field started by Jain et al., (1999), followed by Abrahart and White, (2001) and then again Jain, (2001). The application of ANN in suspended sediment was not as widely researched as the rainfall-runoff modelling, but it showed very interesting contribution by researchers worldwide. According to the study of Afan et al., (2016) around 60 research papers discussed the estimation of suspended sediment by ANN indexed in the Scopus database in the last two decades.

Abrahart and White (2001) used ANN to predict suspended sediment load with rainfall and runoff as inputs, for a series of various land use and management regimes of four experimental catchments in Malawi, and indicated that the ANN approach could give a better fit to the data than multiple linear regression (MLR). Jain (2001) used ANN approach for the prediction of suspended sediment concentration of two sites on the Mississipi River. He observed that ANN approach results are more accurate than the conventional methods. Nagy et al (2002) estimated and forecasted the suspended sediment load using multi layer back propagation algorithm in three different rivers, the Niobrara river, the middle Loup river and the Hii river. The study was carried out on eight different input variables and the performance results of ANN were compared with seven different equation of suspended sediment. The researchers showed that using ANN to forecast suspended sediment is more accurate than other conventional equations. Cigizoglu (2004) investigated the performance of MLP neural network model of two gauging stations in the upstream and downstream of the Schuykill river in Philadelphia, USA. The study was carried out on Daily Mean Flow and Suspended Sediment data of 29 years. Cigizoglu improved his MLP model by employing the upstream sediment series instead of previous downstream records. The author concluded by stating that using NN for the suspended sediment estimation and forecasting is effective because of its non linear nature, He also stated that the MLP model was more accurate than the conventional methods. Alp and Cigizoglu (2007) forecasted and estimated sediment load using the feed forward back propagation and radial basis function. The study was carried out on data of previous rainfall, sediment load and river flow. The used data was from the Juniata Catchment, Pennsylvania USA. The researchers concluded that depending only on rainfall data did not give satisfying results comparing to adding flow data. They also concluded that the results of the back propagation were closer to the radial basis function results. Mellesse et al (2011) compared Back Propagation neural network with Multiple Linear Regresion (MLR), Multiple Non-Linear Regression (MNLR) and Auto-Regressive Integrated Moving Average (ARIMA) models in three big rivers; Mississippi, Missouri and Rio Grande rivers in USA. The study was carried out on weekly and daily- rainfall, discharge, antecedent discharge and antecedent sediment load to predict current sediment load. The study concluded that daily prediction was more accurate than weekly prediction. Moreover, the ANN model gave higher results than other regressive models. Mustafa et al (2012) estimated suspended sediment discharge in the Pari river, Peninsular Malaysia. The authors used a Multi Layer Perceptron Feed Forward Neural Network with four different training algorithms; Gradient Decent (GD), Gradient Descent with Momentum (GDM), Sealed Conjugate Gradient (SCG) and Levenberg Marquadt (LM). The authors recommended touse the Levenberg Marquadt algorithm for the suspended sediment estimation, and they stated that the LM was faster and more accurate than the other algorithms.

Afan et al (2014) estimated suspended sediment depending on daily data of sediment discharge and flow from the Rantau Panjang station on Johor river in Malaysia. The authors compared Feed Forward Neural Network with Radial Basis Function algorithms, and they concluded that the FFNN showed better performance results than the RBF.

From our investigation we can state that the use of ANN for the suspended sediment estimation and forecasting is very robust and effective, and helped the hydrologists to evaluate and contribute in the study of this phenomenon. We can also say that ANN models are more accurate than the conventional methods according to different researches in the last two decades.

IV. EROSION AND SEDIMENTATION

IV.1 SOIL EROSION:

IV.1.1 Introduction:

Water erosion is widespread phenomenon in the watersheds. It is the grignotage of the soil surface by water from raindrop, runoff, snowmelt, and irrigation. The raindrops affect the surface and go in the form of runoff which is the main factor of water erosion. It refers to the loss or displacement of soil degradation along the soil surface with the runoff water and the eroded particles to the aquatic systems or to the grassland. It gives rise to the turbidity and sedimentation in rivers, reservoirs and different hydraulic constructions, and deteriorates the water quality by eroding different bacterial elements that are carried by the soil erosion. For better evaluation and understanding of the mechanism of water erosion it is very important to quantify the soil loss and develop different models and practices for controlling this phenomenon. The aim of this chapter is to describe this phenomenon and different types, of factors and predictive models dealing with water erosion.

IV.1.2 Erosion types:

There are many types of erosion that cause sedimentation and provide the loss of soil, deterioration of water quality, hydraulic construction, and the hydro-systems. In this section bellow we have chosen couple of erosion types that they have affect greatly on the soil loss in the watersheds.

IV.1.2.1 Splash Erosion:

Raindrops affecting the surface dissolve and splash the soil separating the surface particles from their original positions. The soil surface that is impacted by raindrops is caused by the bombardment of erosion splash Ghadiri, (2004). Blanco, (2010) explained the process of splash erosion as followed; the soil surface get strike by a raindrop which is developing a raindrop-soil particle before liberating their energy in splash form. The soil formation changes to craters and cavities because of the shelling by raindrops. The size and shape of the formed craters and cavities matches exactly the raindrops sizes and shapes.

IV.1.2.2 Interrill Erosion:

The Interrill erosion starts when the runoff creates a diminut rills, and that portion of running water between rills is named sheet or interill erosion, this kind of erosion occurs mostly due to shallow flow. The splashed particles are carried by the runoff that runs into small rills. The interill is the most affecting soil erosion in watershed. The splash erosion and interill erosion make up about 70% of total soil erosion Blanco, (2010).

IV.1.2.3 Rill Erosion:

The soil erosion occurs in small channels or rills it is known as the rill erosion. Contrary to the interrill erosion, the rill erosion generally appears because of the concentrated flow not the shallow flow. The eroded soil by the concentrated runoff water in small channels is faster than the interrill erosion. The rill erosion is the second popular pathway of soil erosion, the intensive rainfall can cause large soil erosion, but the cultivation can easily wipe out the rills. Blanco, (2010).

IV.1.2.4 Gully Erosion:

A gully is formed by the runoff water that is eroding into hillslopes creating either V or U shaped valleys in various sizes, from few meters to ten meters in depth and width.

When the force of flowing water exceeds the resistance of the soil eroded, it starts the gully erosion. The entire soil profiles in localized segments of the filed can be removed with permanent gully erosion. The gully erosion is of two types; the first type is *permanent gullies* which are too large to be smoothed by regular cultivating, and they require expensive measures of reclamation and control. The second type is *ephemeral gully* which are small channels that can be easily managed and corrected by conventional tillage equipment Blanco, (2010) and Ffolliot et al., (2013).

IV.1.3 Factors:

The major factors controlling water erosion are precipitation, vegetative cover, topography, and soil properties.

The water erosion is a difficult phenomenon that hydrologists and hydro-geologists are dealing with since many decades. Many factors are affecting and increasing the water erosion in watersheds due to different factors. The water erosion is controlled mainly by four major factors: climatic factors, vegetation cover, topography and soil properties. For better explanation we can quote the explanation from Blanco, (2010) *"the longer and steeper the slope, the more erodible the soil, and the greater the transport capacity of runoff under an intense rain. The role of vegetation on preventing soil erosion is well recognized. Surface vegetative cover improves soil's resistance to erosion by stabilizing soil structure, increasing soil organic matter, and promoting activity of soil macro- and micro-organisms. The effectiveness of vegetative cover depends on plant species, density, age, and root and foliage patterns"*.

IV.1.4 Erosion Quantification:

Different models and equations were introduced by hydrologists for better prediction and quantification of the soil loss that are caused by water erosion to minimize losses in different agricultural lands and protect water resources from the sediments. We mentioned in this section three worldwide known equation and one model that deal with the prediction of the soil loss in watersheds.

IV.1.4.1 Universal Soil Loss Equation:

The Universal Soil Loss Equation (USLE) was developed by the United States Department of Agriculture by Wischmeier and Smith, (1965, 1978). The USLE formula is comprised by the following factors;

$$A = R.K.LS.C.P \qquad (4)$$

A is the computed soil loss expressed in tons by arc during a period of the selected rainfall erosivity factor.

R is the rainfall erosivity factor which is the raindrop impact and the rate of surface runoff associated with rainstorm during a period of a year or a season.

K is the soil erodibility factor which indicates the sensitivity of soil particles resistance to erosion.

LS is the topographic index (LS), which combines two parameters, namely the length of the slope (L) and its inclination (S), which have a significant impact on the runoff regime and consequently on water erosion.

C is the cropping management factor which is integration of factors such as: vegetation cover, plant litter, soil surface and land management.

P is the erosion control practice factor, it reflects the used cultivation techniques and soil conservation measures, which reduces the volume and speeds of the streaming water and promotes infiltration by changing the soil structural state which reduces the erosive impact.

IV.1.4.2 Modification of the Universal Soil Loss Equation:

Wischmeier, (1975) with the Environmental Protection Agency, (1980) has modified the Universal Soil Loss Equation (USLE) to the Modified Universal Soil Loss Equation (MUSLE) for the need to use in the forest and the grassland. Two factors were replaced in the Universal Soil Loss in forming the Modified Universal Soil Loss Equation; the Cropping Management (C) and the Erosion Control Practice (P) by the Vegetation Management factor (VM).

$$A = R.K.LS.VM \qquad (5)$$

IV.1.4.3 The Revised Universal Soil Loss Equation:

The Revised Universal Soil Loss Equation (RUSLE) predicts long-term average annual soil loss erosion by water from specific field slopes in specified cropping and management systems. The RUSL equation was also widely applicable in other nonagricultural conditions sites where the mineral soil has been exposed to raindrop impacts and surface runoff such as mining and construction sites. The Agriculture Research Service of the U.S. Department of Agriculture and their cooperators developed the RUSLE to be applied to single events, to account for the temporal changes in soil erodibility and plant factors that were not originally considered in the formulations of the USLE (Renard et al., 1997; Weltz et al., 1998). The RUSLE technology is computer-based and, therefore, replaces the tables, monographs, and USLE calculations with a keyboard entry. RUSLE has undergone revisions since its original formulation with the current version, called RUSLE2, a computer program that provides estimates of soil loss, sediment characteristics from small channels and sheet erosion, and sediment yield. It also uses a graphical-user interface in its application instead of the text-based interface of earlier versions of the program Blanco et al., (2010).

IV.1.4.4 Water Erosion Project Manager:

The Agriculture Research Service of the U.S Department of Agriculture and their cooperators has developed a new technology called The Water Erosion Prediction Project (WEPP) for predicting the soil erosion by water.

The new model technology estimates soil erosion in different ratio scale; single events, long-term soil loss from hill slopes (gully erosion) and soil detachment and deposition that occurs in small stream channels (Rill Erosion) in watershed Weltz et al., (1998).

The goal of this WEPP effort is a process-oriented model or family of models that are conceptually superior to the lumped-model RUSLE and are more versatile as to the conditions that can be evaluated. The WEPP technology is expected to replace RUSLE sometime in the future Renard et al., (1997).

IV.2 SEDIMENT TRANSPORT IN STREAMS:

IV.2.1 Overview:

Sediment transport in rivers is the second phase of water erosion, sediment movement in streams and rivers takes two forms up to the rate and energy of the runoff and the size of particles, the intensity of rainfall, the soil characteristics and topography of the watershed and streams, are all affecting factors that divide the sedimentation in rivers and streams into sediment suspension load or bed load.

The division between the bed load and the suspension depends essentially on the particles sizes related to the water velocity and the turbulence of the flow.

The sediment supply is the product of soil erosion defined by the characteristics of the hydrological parameters in the watershed whether it occurs as surface erosion, gully erosion, soil mass movement or channel erosion.

IV.2.2 Suspended Load:

The transported particles of the soil can be the same such as suspended load transport if the settling velocity of the particles is lesser than the buoyant velocity of the turbulent eddies and vortices of the water. The size and density of particles impact strongly on the settling velocity.

The settling (sediment) velocity of particles with diameter < 0.1 mm is comparative to the square of the particles diameter, while the settling (sediment) velocity of particles with a diameter >0.1 is comparative to the square root of the particle diameter. The suspension load needs only little energy to transport particles in suspension. The decreased turbulence in streams is caused by the heavy load of suspended sediment. It also confirmed that the highest concentration in shallow streams is caused by high velocities. However, the highest concentration of suspended sediment is highly concentrated with stream depth and decreases near the water surface. The soil particles with a diameter <0.005 mm such as (silt and clay) are generally dispersed uniformly throughout the stream depth, but the big particles are more concentrated near the bed river.

This is the general theory that confirms the correlation between suspended sediment concentration and stream flow discharge in most rivers. As the peak passes and the rate of stream flow discharge drops, the quantity of suspended sediment also reduces quickly and aggradations occurs Brooks et al., (2013). The development of sediment rating curve is based on the relationship of the measurement sediment concentration and stream flow discharge data Ffuliot et al., (2013).

IV.2.3 Bed load:

The Bed Load Transport is one of the main types of sediment transport in rivers, it refers to the biggest particles that impact on the formation and the balance of river bed, exactly the slope Mokhtari, (2010). The bed load particles transport singly or in groups and can be entrained if the vertical velocity of eddies creates sufficient suction to lift the particle from the bottom. These particles can also be placed in motion if the force exerted by the water is greater on the top of the grain than on the lower part Brooks et al., (2013).

The bed load means the sediment transport in the bed river, it has a serious problem in the regularization of rivers flows and in the hydro-technical construction.

Many researchers studied the bed load phenomenon in the bed river, different theories and experimental were applied, but still there is not a general universal theory that can help to understand the exact mechanism of this phenomenon.

One of the first researchers that studied the bed load phenomenon is De Boys, (1879), and then around 50 years later in 1930 different researches such as Meyer-Peter, Einstein and Muller, whom started contributing theories on this phenomenon depending on their work on the particles balance in runoff of river system, for a regular shaped channel. The different theories weren't for direct application on rivers with non uniform runoff and non sized channels Ffuliot et al., (2013).

IV.2.4 Different methods of estimating SSD in reservoirs:

IV.2.4.1 Bathymetric survey:

A bathymetric survey is a very effective tool for measuring the volume of trapped sediment in a reservoir, the total suspended sediment is mainly measured in the long term by repeated bathymetric surveys, because it takes into consideration the solid flow in suspension, and it is carried materials. The major uncertainty concerning this method is that of the apparent density of Sediment that is generally estimated and not measured, which can vary considerably not only according to the depth but also from one survey to another (Morris and Fan 1998; Tebbi et al, 2012).

IV.2.4.2 Sediment rating curve:

The sediment rating curve (SRC) is an empirical relation between water discharge and sediment concentration (or sediment discharge) which can be expressed by (different regression equations; empirical law equation, the power law equation, the log equation) Jain, (2012).

Tebbi et al, 2012 stated that sediment rating curve is Black Box type model that is not related directly to any physical parameters. The empirical equation is expressed as follows:

$$C = aQl^b \quad (6)$$

$$QS = a'Ql^{b'} \quad (7)$$

The coefficients of both equations a, b, a′ and b′ are empirically determined. According to Morgan (1995) the coefficients a, a′ represents the erodibility of soils in watersheds. The b coefficients signify the erosive power of the river (Asseleman, 2000). And according to Walling 1978 the grain size of the material that transported by the river refer to the coefficient b.

IV.2.4.3 Trap efficiency:

The trap efficiency method is calculating the percentage of total solid intake in the reservoir. The method is found by Brune, (1953) and it is widely used by scientists all over the world Arega & dawarakish, (2016). This method estimates this efficiency by the development of the curve with the relation between trap efficiency and reservoir capacity-inflow (C/I) ratio Batuca and Jordaan, (2000); Heinemann (1984); Arega & dawarakish (2016).

IV.2.5 Overview of the suspended sediment transport in Algeria:

Suspended sediment flux in a river is an important parameter for the management of hydraulic projects, and an index for the status of soil erosion and ecological environment of a catchment Zhu et al., (2007). The problem of availability of data on sediment transport is acute in Algeria, and direct measurement to quantify sediment discharge is difficult and needs sufficient time, money and daily maintenance. An effective and fast estimation of sediments in watersheds are ones of great interests for large number of engineering applications to protect hydraulic infrastructure from different disasters such as: stability problems, the loss of water storage in reservoir and the deterioration of water quality. According to (Remini, 2004; Remini et al., 2009) the erosion rate is between 2000 and 4000 t/km2/year. The average annual amount of deposited sediment in dams passed from 20 million m3 in the 80's to 35 million m3 in the 90's and reached 45 million m3 in 2000 (Serbah, 2011). The suspended sediment discharge in Algeria is estimated at the hydrometric stations of watersheds for substantially all episodes of flow. The increase of suspended sediment load and its sedimentation in Algeria led hydrologists to research the phenomenon of suspended sediment discharge and its relation with some of the hydro-climatic parameters, such as rainfall, runoff, land cover, and sediment concentration in different rivers. We can cite couple of works: "Medinger (1960), who proceeded to the treatment of thirty basins of the first series of measures collected in

Algeria during the period 1946 – 1957; Tixeront (1960), who based its research on the content of suspended sediment in Algerian and Tunisian Rivers with 32 and 9 hydrometric stations, respectively; Demmak (1984), who obtained an empirical relationship between sediment discharge and catchment physico-climatic parameters during period of 10 years in some of the northern watersheds in Algeria; Meddi et al (1998), who used in their work data of 18 reservoirs with 50 hydrometric stations in Algeria, 16 Moroccan reservoirs and 11 Tunisian reservoirs to improve a model which estimates suspended sediment load in northern Algeria.

Many researches that have shown in their researches the quantification of suspended sediment discharge using the most used method in Algeria the sediment rating curve. The researchers used different hydrological parameters to estimate and predict the sediment discharge in different Algerian rivers. The table bellow shows most of the enumerated papers dealing with this phenomenon.

Table IV-1 Different studies for estimating the suspended sediment in Algeria.

References	Rivers	Technique	Duration
Terfous, 2001	Wadi Mouilah	SRC	16 years
Meddi, 1999	Wadi Ebda	SRC	5 years
Achit et Meddi, 2004	Wadi Haddad	SRC	22 years
Benkhaled et Remini, 2003	Wadi Wahrane	SRC	18 years
Achite et meddi, 2005	Wadi Mina	SRC	22 years
Lefkir et all, 2006	Isser River	SRC & ANFIS	3 years
Larfi and Remini, 2006	Isser River	SRC	13 years
Khanchoul, 2006	Safsaf , Mellah, Ressoul	SRC	22 years
Megnounif et al, 2007	Upper Tafna	SRC	5 years
Cherif et al. 2009	Wadi Mekkara	SRC	8 years
Khanchoul, 2009	Wadi Mellah	SRC	24 years
Touaibia, 2010	Wadi mouileh	SRC	18 years
Elmahi et al, 2012	Wadi Elhammam	SRC	8 years
Boucheklia et al 2013	Wadi Tafna	SRC	11 years
Louamri et al 2013	Wadi Bouhamdane	SRC	18 y + 15 y

IV.3 THE MODEL DEVELOPMENT:

IV.3.1 Standard Back Propagation neural network:

IV.3.1.1 Available data and normalization:

The available daily data sets were comprised of water discharge ($m3 \cdot s^{-1}$), suspended sediment concentration ($g \cdot l^{-1}$) and suspended sediment discharge ($kg \cdot s^{-1}$) from the period between 1 September 1971 and 31 August 2001. The data used in this article come from the National Agency of Water Resources (ANRH).

Because of different measurement units, we have applied normalization using equation (1) to prevent the effect of extreme values of the data sets and to match the sigmoid type of transfer function, which has a range of values varying from 0 to 1.

The input and output data were normalized using the following transformation equation:

$$Y_{norm} = Y_i / Y_{max} \qquad (8)$$

Where Y norm is the normalized dimensionless variable, Yi is the observed value of variable; Y max is the maximum value of the variables.

IV.3.1.2 Data dividing:

The data series were divided on Three sets; In the wadi of Isser; we used twenty four years for training period (80%) from 1 September 1971 to 31 August 1995 and we used three years (10%) for the validation period from 1 September 1995 to 31 August 1998, and the last three years (10%) were used for testing period from 1 September 1998 to 31 August 2001. In the wadi of Sebaou we used seven years for training period (80%) from 1st September 1978 to 31st August 1985, to avoid over training in the presented networks we used 1 year (10%) for the validation set for cross-validation from 1st September 1985 to 31st August 1986. The last year (10%) between 1st September 1986 and 31st August 1987 was used to assess the performance of the model.

IV.3.1.3 Choosing the neural network architecture:

- **The chosen inputs variables** in the presented study are due to the straight relation between water discharge and sediment discharge. Taking under consideration that the estimation formula of sediment discharge in Algeria is SSD = SSC * WD. Where SSD is suspended sediment discharge (kg/s), SSC is the measured sediment concentration (g/l) and WD is the water discharge measured in river (m^3/s) or obtained by the flow curve duration formula. The used previous values of water discharge and sediment discharge are chosen in order of understanding the relation between sediment discharge and different previous values of water discharge and sediment discharge, in the other hand for improving the prediction and estimation of sediment discharge in rivers.

- **The input combination:** the used inputs in the presented model were the current and previous values of water discharge and previous values of the suspended sediment discharge. Eight input combination were applied using the back propagation algorithm with different neural network architecture. In the following points we explain each input combination and its architecture:

ANN 01: the first input combination we used the current water discharge (WD) to predict the sediment discharge (SD). The neural network model consists of one input layer (WD), two hidden layers (the first hidden layer with '*tansig*' transfer function. In the second hidden layer with '*logsig*' transfer function) and output layer (SSD) with a logsig transfer function (table).The architecture type of the model is feed forward neural network.

ANN 02: the second input combination it depends on previous sediment discharge (SSD_{t-1}). The NN model consists of input layer (SSD_{t-1}), two hidden layers (the first hidden layer is '*tansig*' transfer function. In the second hidden layer is neurones and '*logsig*' transfer function).

ANN 03: the third neural network model depend on two inputs current water discharge (WD_t) and previous water discharge (WD_{t-1}). The hidden layers are comprised from two layers; the first layer with '*tansig*' transfer function and the second layer with a '*logsig*' transfer function.

ANN 04: the input combination in ANN 04 is based on current water discharge (WDt) and previous sediment discharge (SDt-1). In the two hidden layers two transfer functions are used, the first is '*tansig*' and the second is '*logsig*'.

ANN 05: the fifth input combination is based on the values of previous and two previous sediment discharges (SSD_{t-1}, SSD_{t-2}). The transfer function in the first layer is '*tansig*' and in the second layer is '*logsig*'.

ANN 06: the input combinations in this ANN are current water discharge (WD_t), previous sediment discharge (SSD_{t-1}) and two previous sediment discharge (SSD_{t-2}). The same transfer function like the previous ANNs in the two hidden layers and the output layer for predicting suspended sediment discharge.

ANN 07: in the ANN 07 we tried current and previous water discharge (WD_t, WD_{t-1}) and previous sediment discharge (SSD_{t-1}), two hidden layers with their transfer function in both layers '*tansig*' and '*logsig*' respectively.

ANN 08: current and previous water discharge (WD_t, WD_{t-1}) and two previous values of sediment discharge (SSD_{t-1}, SSD_{t-2}) were used in the input combination of this ANN. Two hidden layers were used in this model with the same previous transfer function that was used in the previous ANNs.

- **Training NN:**

After the neural network being structured and the training function was chose (LM), for these particular applications the network is ready to be trained. In this ANN models both the inputs and outputs data for this period are known and fully introduced to the model. The networks start processing the inputs and compare its output resulting to the desired outputs that were introduced to the models. The training set is used to train the Neural Network by minimizing the error of the data and finding its best performance. The data used in this period it is only introduced to the training process, and it is not introduced to the validation neither to the test sets.

- **Validating NN:**

  The validation set is used for checking the overall performance of the trained network. The validation set is asses for obtaining the chosen network. The validation and test are for the same role in standard neural network model. The purpose of the validation set in this application is for the cross validation technique 'early stopping' that it is used in this application to avoid over fitting which is described in the next section.

- **Testing NN:**

The testing set has the same role like validation set in standard neural network, the testing set is used for checking in general the performance results of the networks that were obtained during the training set.

IV.3.2 The developed neural network model using the early stopping technique:

IV.3.2.1 The BP developed model:

In the first application, the suspended sediment discharge were predicted and estimated with full iteration (500 epochs) that was given to the BP model to assess the best performance during training period. The second application is the development of the standard BP model using the early stopping technique based on different researches were done in literature (Sjoberg and Ljung 1992, Ammari et al 1996, Prechlet 1998, Orr and Müller, 1998, Khadir, 2005 and Piotrowski et al 2014; Tachi et al., 2016). For better explanation, the same BP model that was running was searching the best neural network based on the cross validation. The development of this model was to avoid the over-training that usually occurs often in the standard back propagation neural network models.

IV.3.2.2 The steps of the early stopping technique:

- Partitioning the data set into three parts; training, validation and testing sets, the data were divided into 80%, 10% and 10% respectively.
- The validation set was used only to evaluate the error during training set once in a while, knowing that we used only training set for training.
- The quadratic error was used to determine to errors of both training and validation sets together for detecting the best neural network during the full iteration of the back propagation model.
- To avoid Early Stopping on the validation error that may still go further down after it has begun to increase, we let the training iterations finish with a condition given to our model to save the network with the lowest generalized error (Global Minimum) that was evaluated and compared in every epochs.
- The model shows two different networks in every input combination that were tried, the first network shows the results of the predicted sediment

discharge using standard back propagation algorithm and the second network shows the results of the predicted sediment discharge based on the standard back propagation using the early stopping technique to avoid over-training.

IV.4 THE ESTIMATION OF SEDIMENT DISCHARGE IN UNGAUGED CATCHMENT:

IV.4.1 Overview:

The estimation and prediction of suspended sediment is very required in watersheds where the field data are limited (Bray and huixi, 1993). Most of used data to estimate suspended sediment in catchment are rainfall, water discharge, sediment concentration and sediment discharge. The process of suspended sediment discharge is highly variable by time and location (Bray and huixi, 1993; Morehead et al, 2002). Couples of studies were applied for predicting different hydrological phenomenon in ungauged catchments. Comparing to the application in gauged sites it is very limited due to time variation and different factors that contribute directly to erosion and sedimentation in rivers. Mostly in forecasting the suspended sediment in ungauged sites the artificial intelligence is more applied comparing to the classical regression.

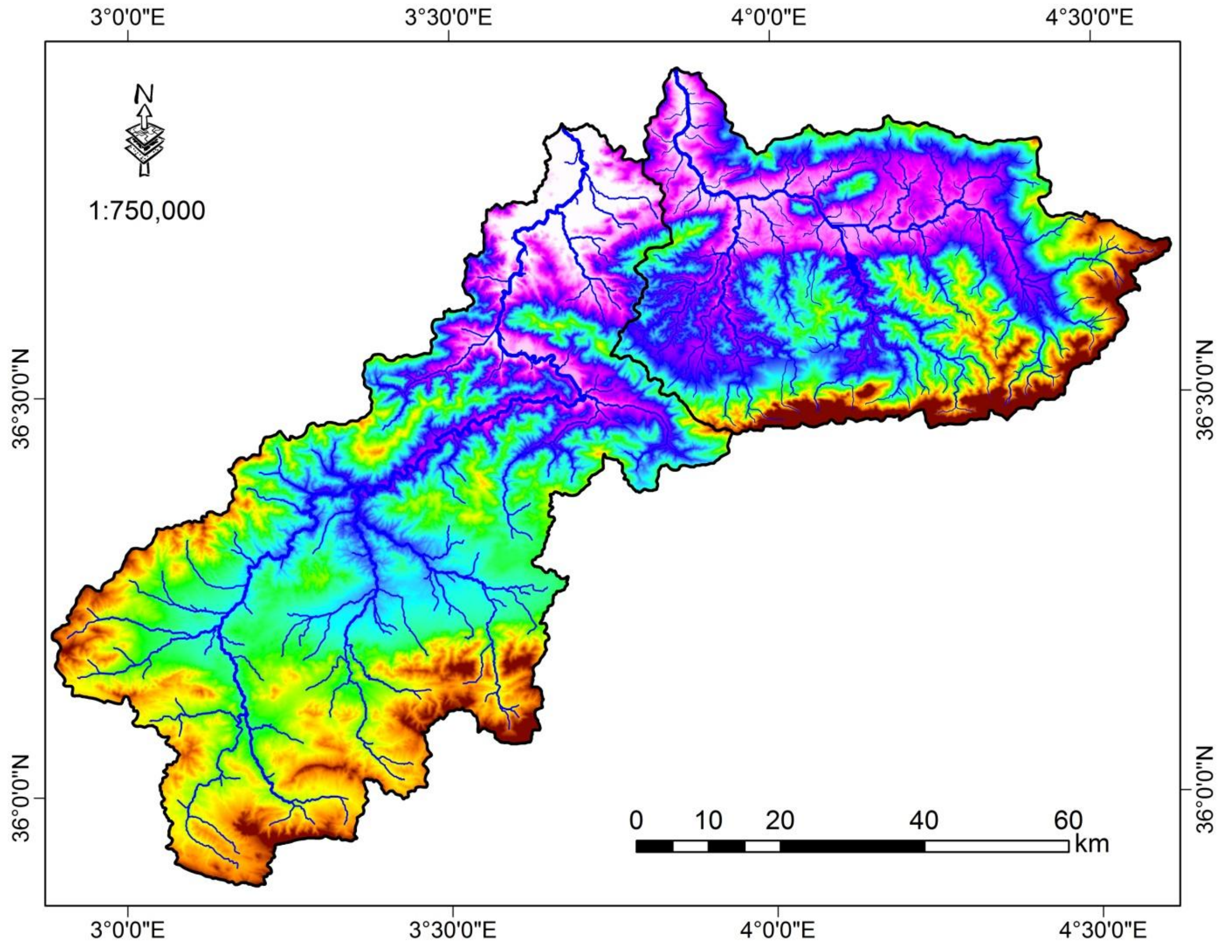
Table IV-2 The literature of predicting different hydrological variables in ungauged catchment.

AUTHORS	METHODS	VARIABLE(s)
Bray & Huixi, 1993	Regression	Suspended Sediment
Cigizoglu H K, 2001	ANN	Suspended Sediment
Morehead, 2002	Rating relation	Suspended Sediment
Dawson et al, 2006	ANN	Flow Discharge
Abrahart et al, 2008	ANN	Suspended Sediment
Lefkir, 2010	Neuro-Fuzzy/ Rating curve	Suspended Sediment
Besaw et al, 2010	ANN	Stream Flow
Heng & Suetsugi, 2013	ANN	Suspended Sediment
Li et al, 2014	SIMHYD/ GR4j	Runoff
Zhang et al, 2015	Flow duration curve/Rainfall-Runoff modeling	Runoff

The estimation and prediction of suspended sediment in ungauged catchment is itself challenging and highly required for engineers. The estimation of suspended total load needs time, accurate measures, money and professional engineers and tools. In this work we presented the developed both models that were applied on the both rivers; the standard back propagation neural network and the back propagation neural network with early stopping technique. The forecasting of suspended sediment was carried out on the current and previous water discharge and previous values of suspended sediment discharge of nearby watershed. The forecasting of suspended sediment discharge in ungauged catchment was based on couple of studies; Lefkir, (2009), Cigizoglu H K, (2001) and Dawson et al, (2006), in order of regionalizing and understanding the suspended sediment phenomenon in rivers, and for better estimation and flood forecasting in different ungauged rivers.

IV.4.2 The data analysis of the un-gauged catchments:

The developed model in forecasting the suspended sediment load in ungauged catchment is for improving the ability of predicting the suspended sediment load in rivers. First in this application, we tried to predict sediment discharge in the sebaou river depending on the input data of the isser river, the data were carried on daily suspended sediment discharge and water discharge. The training data of this application were depending on the input combination of current and previous values of water discharge and sediment discharge of the Isser river of 7 years between 1st September 1978 and 31st August 1985. The validation and testing periods of this application were carried out on the data from the Sebaou wadi between 1st September 1985 and 31st August 1986 and from 1st September 1986 to 31st August 1987 respectively. In the second application in the ungauged catchment we tried to forecast the sediment load in the Isser wadi using input data of the sebaou. The training data of the sebaou that were used in the isser are from 1st September 1971 to 31st August 1985. The validation and testing periods are from 1st September 1985 to 31st August 1986 and 1st September 1986 to 31st August 1987, respectively.



IV.1 the watersheds of the Isser and Great Kabyle.

The watersheds of both studied valleys (Isser and Sebaou) are nearby watersheds as it is shown in (figure VI.1). The watersheds have the same climatic and hydrological characteristics. The geological sides of watersheds are closely similar as it is illustrated in figures in the section of studied areas (soil map II.5 and II.14).

V. RESULTS AND DISCUSSION:

In general, the training, validation and testing are the fundamental steps of Neural Network process. The training set is used to train the Neural Network by minimizing the error of the data and finding its best performance. Then, the validation and testing sets are used for checking the overall performance of the trained network. The Feed Forward Back Propagation Neural Network is the most common algorithm for multi-layered networks, which is often used in hydrologic modelling. It consists of an input layer, two hidden layers and an output layer; the numbers of neurons in the hidden layers is a very difficult task for Multi Layer Perceptron method. The performance of the Back Propagation model was tested for two different applications on two different studied areas.

In the first application, the suspended sediment load was predicted and estimated with full iterations that were given to the BP model to assess the best performances during training period. In the second application the sediment load was predicted using the “Early Stopping” technique which depended on the best network during the same iterations. A different numbers of input combinations were tried by BP model and the performances were compared to each other for the best input combination that gave the best values of RMSE and R^2.

V.1 FORECASTING SUSPENDED SEDIMENT IN THE ISSER RIVER:

The suspended sediment discharge were trained, validated and tested by regularised and non regularised neural networks using the data of the Isser Wadi. The modelling of the sediment discharge was based on daily scale. The data of the Isser Wadi were comprised of water discharge m^3/s (measured), sediment concentration g/l (measured) and sediment discharge kg/s (calculated) during a period of thirty years from 1st September 1971 to 31st August 2001. The data sets were divided into three sets, 80% for training period, 10% for cross validation and 10% for testing period. Two different applications were used to forecast sediment discharge. Table V-1 represents the application of the presented models using non regularized neural networks, and table V-2 represents the second application using the regularised neural networks.

V.1.1 Forecasting Suspended Sediment Discharge using Non Regularized Neural Network:

Table V-1 The performances of the non regularized neural network during training, validation and testing periods depending on current and previous water discharge and previous sediment discharge.

ANN	INPUT COMBINATION	Training		Validation		Testing	
		RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_1	WD_t	6.50	56.3	7.62	56.7	3.32	75.5
ANN_2	SSD_{t-1}	8.07	31.1	9.76	29.9	6.29	05.8
ANN_3	WD_t, WD_{t-1}	5.91	64.5	7.62	57.7	**2.57**	**84.4**
ANN_4	WD_t, SSD_{t-1}	5.28	71.5	6.47	69.7	5.71	24.9
ANN_5	SSD_{t-1}, SSD_{t-2}	8.07	32.6	10.45	19.1	6.47	01.8
ANN_6	WD_t, SSD_{t-1}, SSD_{t-2}	5.71	65.6	9.02	40.1	4.62	49.6
ANN_7	WD_t, WD_{t-1}, SSD_{t-1}	**3.27**	**88.8**	**5.50**	**77.9**	3.07	77.7
ANN_8	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	3.61	86.3	6.99	64.1	3.66	68.4

The RMSE and R^2 values of the training, validation and testing period of the non regularized networks are represented in Table V-1, the BP networks are trained according to the Levenberg-Marquardt algorithm, with input layer, two hidden layers and output layer, with full iteration (500 epochs) for each network (8 networks).

The performance values of the training period show very good results of ANN_7, _8, _4 with R^2 (88.8%, 86.3%, 71.5%) respectively. The ANN_6, _3 and _1, showed acceptable values as well with R^2 (65.6%, 64.5%, 56.3%) respectively.

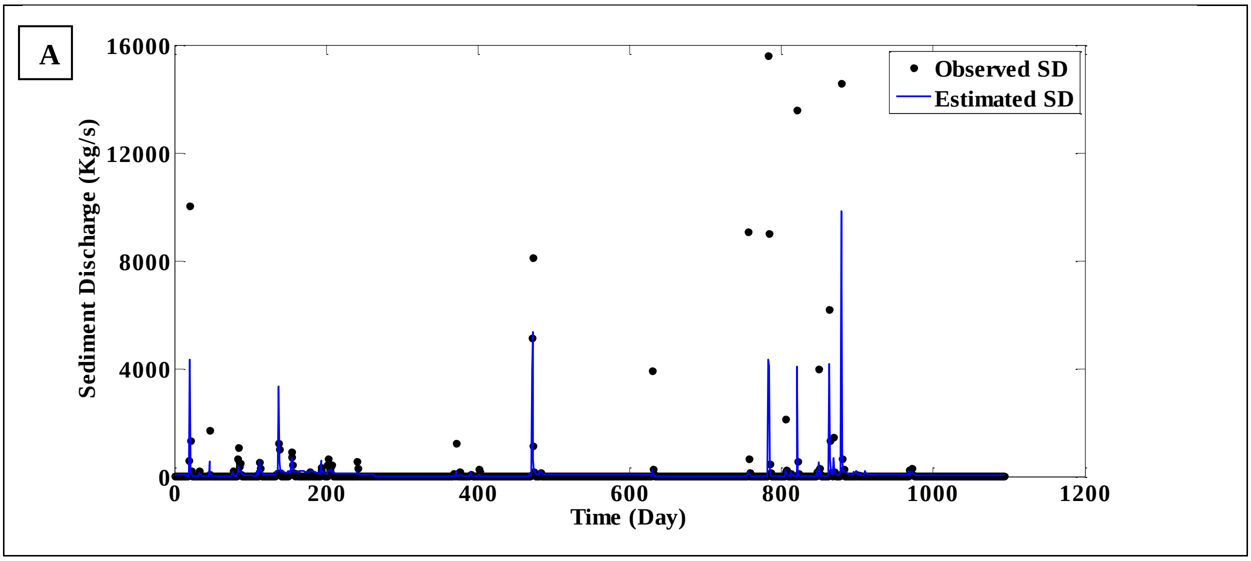
The relation between input combinations and output during training process showed good values in the networks 7 and 8. Current and previous water discharge and sediment discharge showed good learning process in the network 7 with (current, previous WD and previous SSD), network 8 (current, previous WD and two previous SSD) and network 4 with (current WD and previous SSD). In the networks 1, 3, 4 and

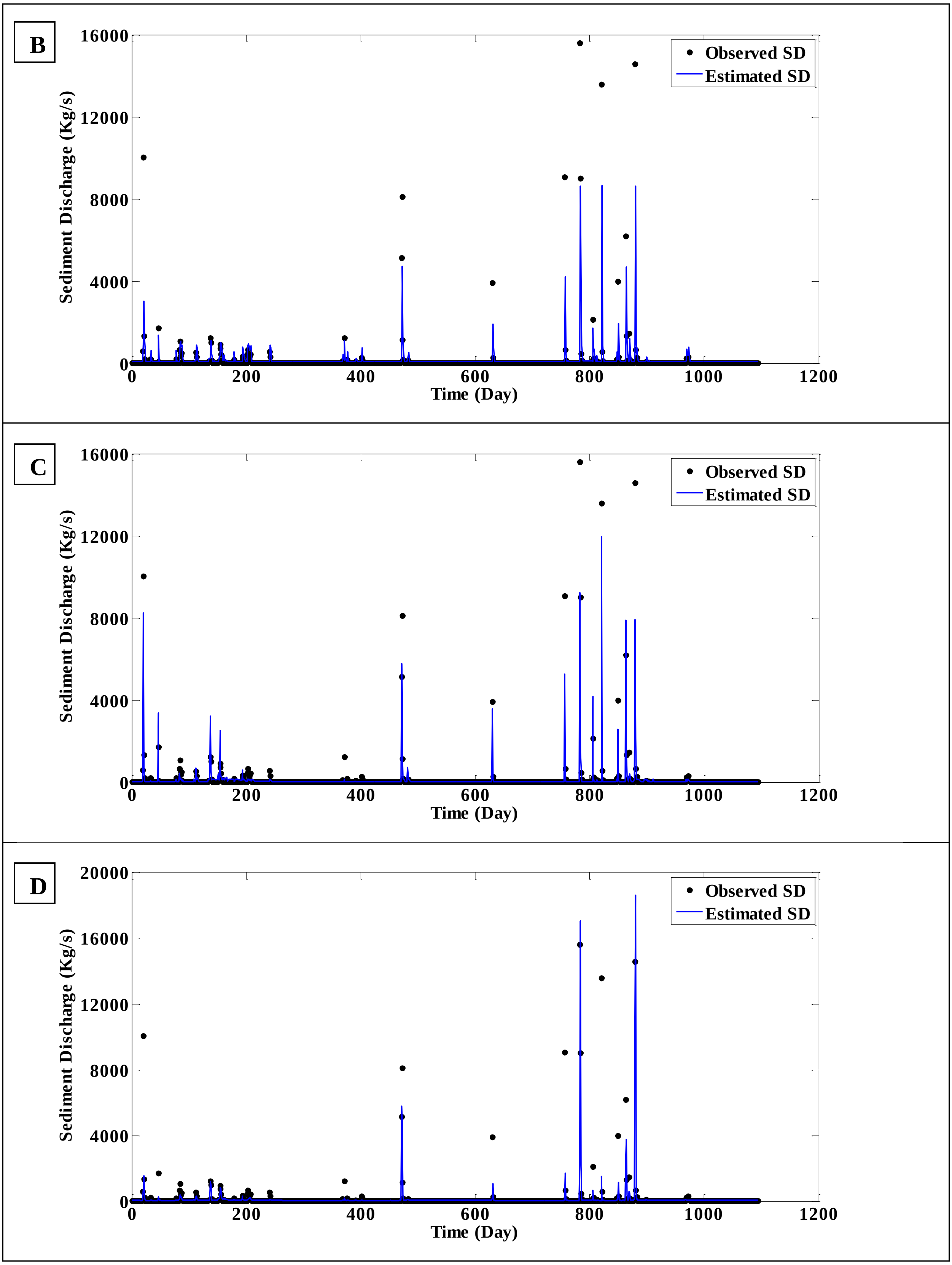
6, the relation between input combination and output showed acceptable values during the learning process but the relation was poor in the networks 2 and 5.

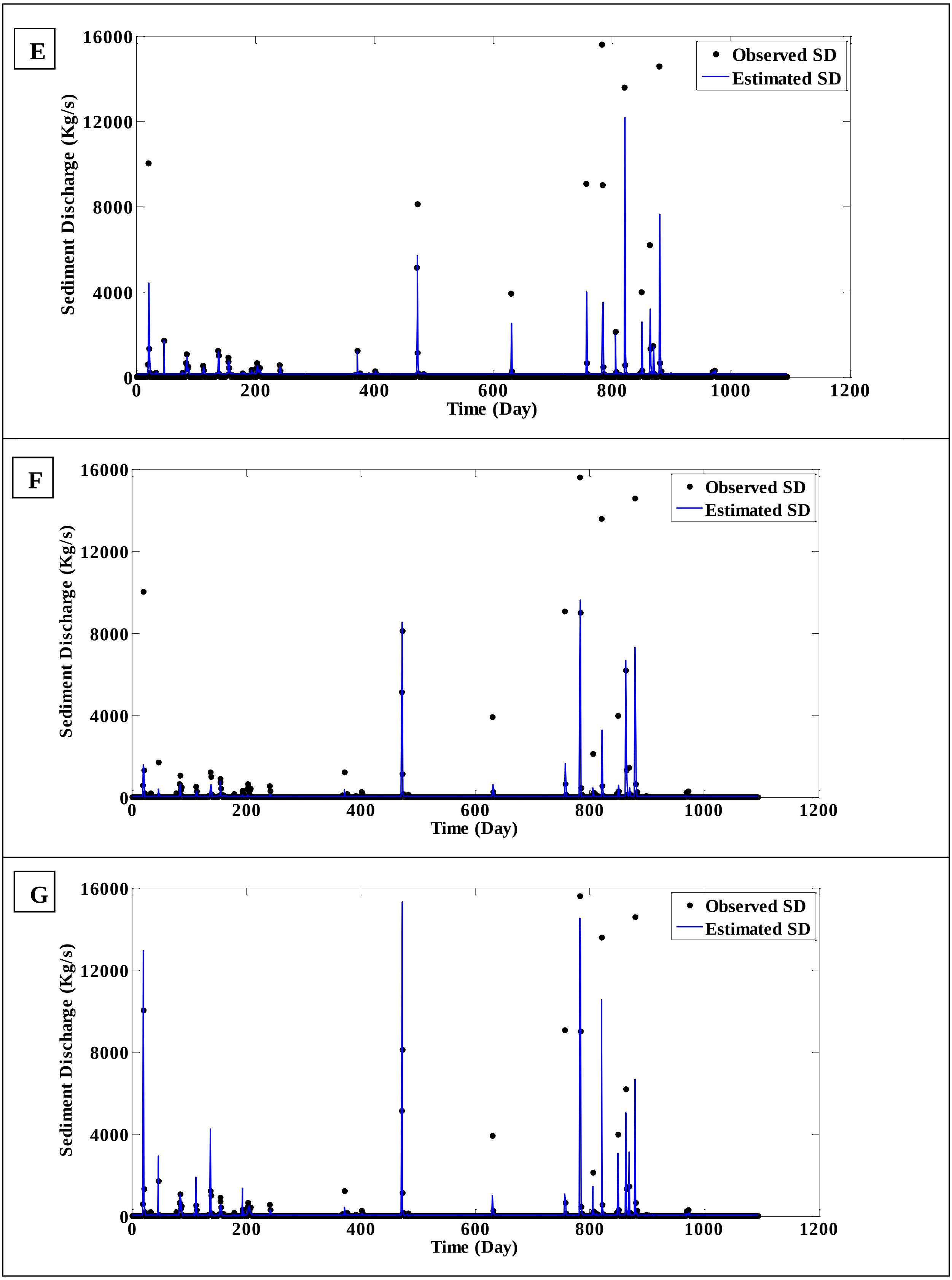
The models evaluation (RMSE and R^2) during testing period in this application (with full iterations), shows that the network with current and previous water discharge ANN_3 (Fig V.1c) gave the best performances with the lowest RMSE (2.57) and the highest R^2 (84.40%), and we can notice that the performance results of ANN_3 during testing period was better than training and validation period (see table V-1). The ANN_7, _1 and _8 gave acceptable results and close values to ANN_3, with RMSE (3.07, 3.32, and 3.66) and R^2 (77.7%, 75.5%, and 68.4%) respectively (Figs V.1). Both BP models with previous sediment discharge ANN_2 and the network with two previous sediment discharge ANN_5 gave the worst values because of the complexity of the data and the poor correlation between input combination and the output, contrary to the other models which proved the positive relation between water discharge and sediment discharge.

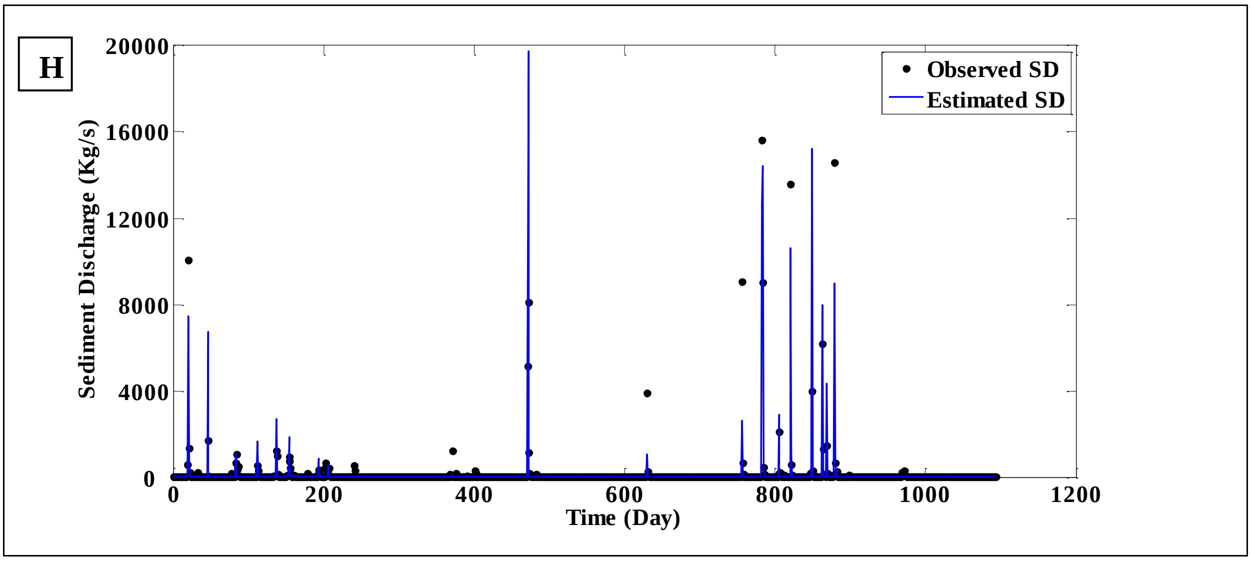
According to the results obtained in this application using the standard back propagation neural network we can notice that the relation is highly strong between current, previous water discharges as input combination versus the sediment discharge. Using current, previous water discharges and previous sediment discharge showed also good estimation of suspended sediment.

Figure V.1 The estimated and observed SSD using non regularized NN in the Isser Wadi.




B
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
4000
8000
12000
16000
0
200
400
600
800
1000
1200
Time (Day)
C
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
4000
8000
12000
16000
0
200
400
600
800
1000
1200
Time (Day)
D
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
4000
8000
12000
16000
20000
0
200
400
600
800
1000
1200
Time (Day)


E
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
F
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
G
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)


H
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
20000
16000
12000
8000
4000
0
200
400
600
800
1000
1200
Time (Day)

V.1.2 Forecasting Suspended Sediment using Regularized Neural Network:

Table V-2 The performances of the regularized networks "Early Stopping criteria's" during training, validation and testing period.

ANN	INPUT COMBINATION	Epoch	Training		Validation		Testing	
			RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_9	WD_t	10	6.50	55.4	7.50	58.4	3.21	75.7
ANN_10	SSD_{t-1}	91	8.07	31.0	9.76	30.0	6.29	05.6
ANN_11	WD_t, WD_{t-1}	85	5.91	62.4	6.99	63.4	**2.53**	**84.9**
ANN_12	WD_t, SSD_{t-1}	07	6.10	60.9	6.47	69.0	4.11	60.1
ANN_13	SSD_{t-1}, SSD_{t-2}	11	8.21	28.7	9.76	30.3	6.28	05.2
ANN_14	WD_t, SSD_{t-1}, SSD_{t-2}	96	6.10	61.3	7.92	53.6	4.75	46.6
ANN_15	WD_t, WD_{t-1}, SSD_{t-1}	41	**3.87**	**84.3**	4.82	82.6	2.71	82.6
ANN_16	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	52	4.03	83.0	**4.61**	**84.4**	2.73	82.4

Table V-2 shows the results of the training, validation and testing periods using the Early Stopping criterion based on cross validation technique.

The networks ANN_15 and 16 gave the best performance results during training period with R^2 (84.3%, 83.0%) respectively. The networks ANN_11, 12 and 14 gave acceptable values during training period with R^2 (62.4%, 60.9%, and 61.3%). We can notice that the networks of the second application during training period was chosen according to cross validation technique, and the performances values were lower than non regularized networks in the first application with full iteration (500 epochs). The relation between input combination and output during training period using the early stopping technique shows lower correlation comparing to the previous correlation using standard back propagation neural network. The explanation of this last one it goes to the stopping training that we did according to the early stopping technique to avoid over-training. The results are shown in table V-2 of the training period is simulated by the network of the stopped iteration.

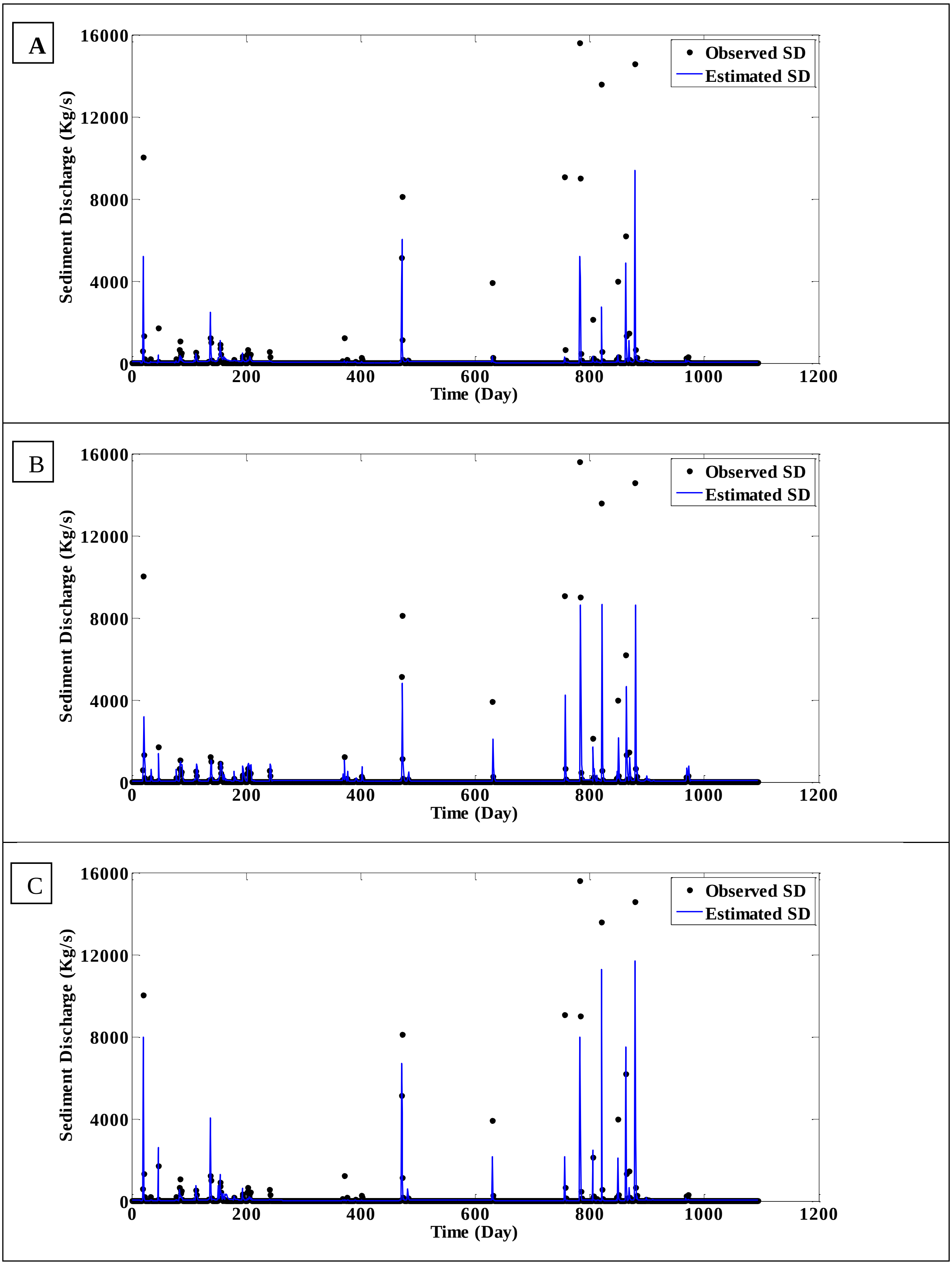
For effective evaluation of the model's result, we used the validation period only for cross validation, but we can see that it is clearly improved comparing to the results of the models of the validation period without regularizing the networks (see table V-1, V-2). We can notice that ANN 15 and 16 gave very good results comparing to the non regularized network with R^2 82% and 84% respectively. The input combination during validation period of the best networks (15 and 16) with current, previous water discharges and previous sediment discharge for ANN 15, and current, previous water discharge and two previous values of sediment discharge gave very strong correlation with the estimated sediment discharge.

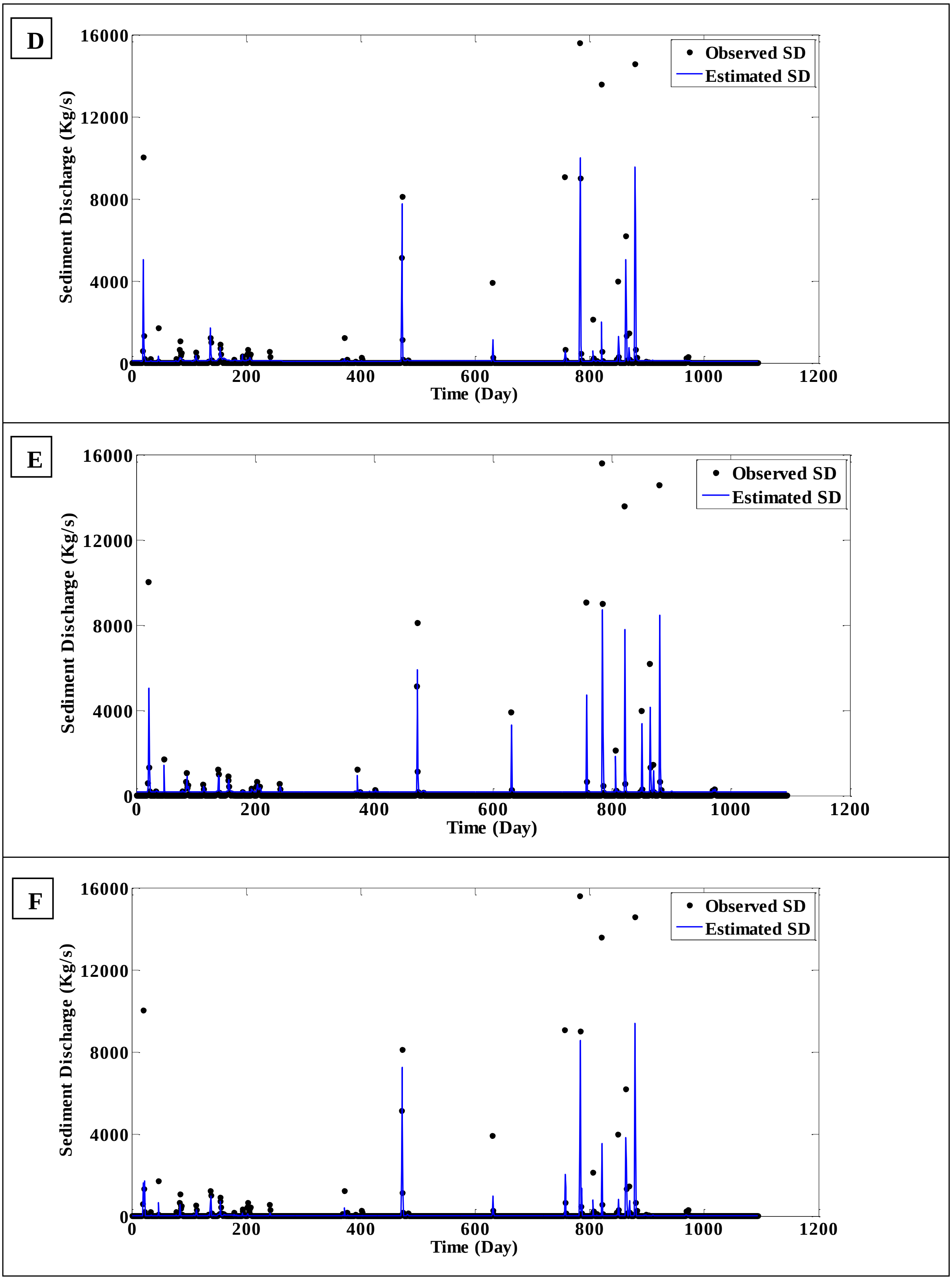
The RMSE and R^2 values of the testing period (Table V-2) were significantly improved as well, the ANN_11 (Fig. V.2) gave the best results with RMSE (2.53) and R^2 (84.9%). The network with current water discharge and previous water discharge and sediment discharge ANN_15, and the network with current water discharge, previous water discharge and two previous sediment discharges ANN_16 showed well goodness of fit (see Figure V.2G and V.2H), and close values to ANN_11 with RMSE (2.71, 2.73) and R^2 (82.6%, 82.4%) respectively.

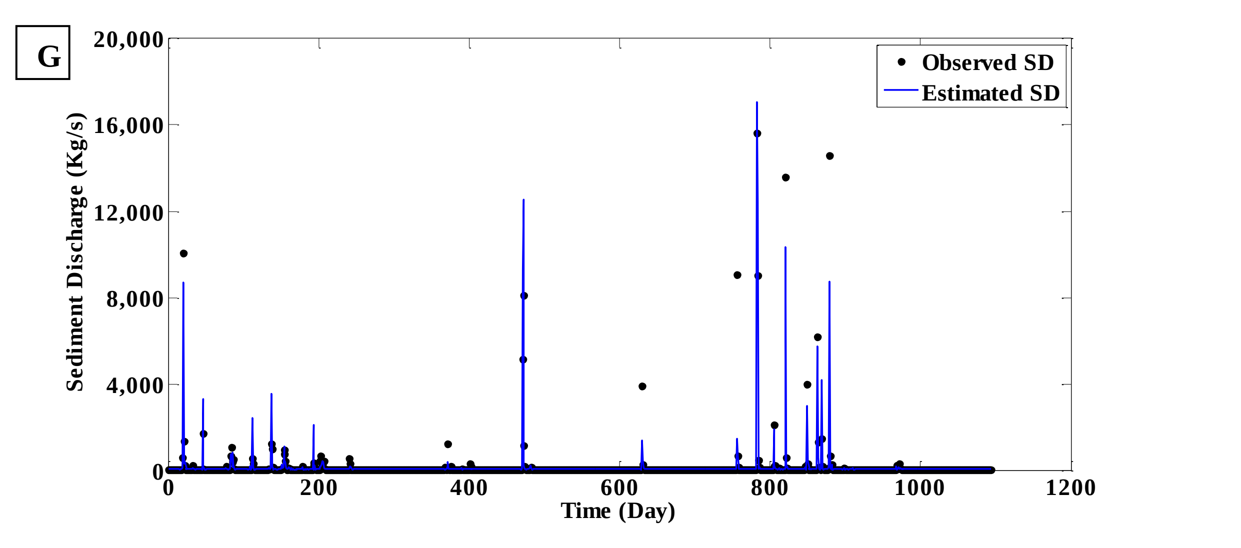
During testing period the results shows that ANN 11 shows the best link between input combination and output proving the relation between current and previous water discharge with the sediment discharge. Comparing ANN 09 using only current water discharge and ANN 11 using current and previous values of water discharge to predict sediment discharge showed that the use of previous water discharge with current discharge improved the prediction of the sediment discharge.

We can notice from all regularized and non regularized networks, that the simulated values over-predict the observed values during small events. Contrary, during the largest events the values are under-predicted. We can also notice from the presented results that the predicted sediment discharge showed high goodness of fit in ANN_3, _7, _8, _11, _15 and _16, opposite to the other networks that showed poor values during flood period. We can also notice that the over training starts in the first 100 epochs for all networks as it is shown in (Table V-2). The results presented in Table V-1 and V-2 showed that over-fitting occurred in the MLP model. We can see that most of the obtained networks were improved when we used cross validation technique.

Figure V.2 The estimated and observed SSD using regularized NN in the Isser Wadi.


A
B
C
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
0
4000
8000
12000
16000
0
200
400
600
800
1000
1200


D
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
E
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
F
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)


G
20,000
16,000
12,000
8,000
4,000
0
Sediment Discharge (Kg/s)
0
200
400
600
800
1000
1200
Time (Day)
Observed SD
Estimated SD

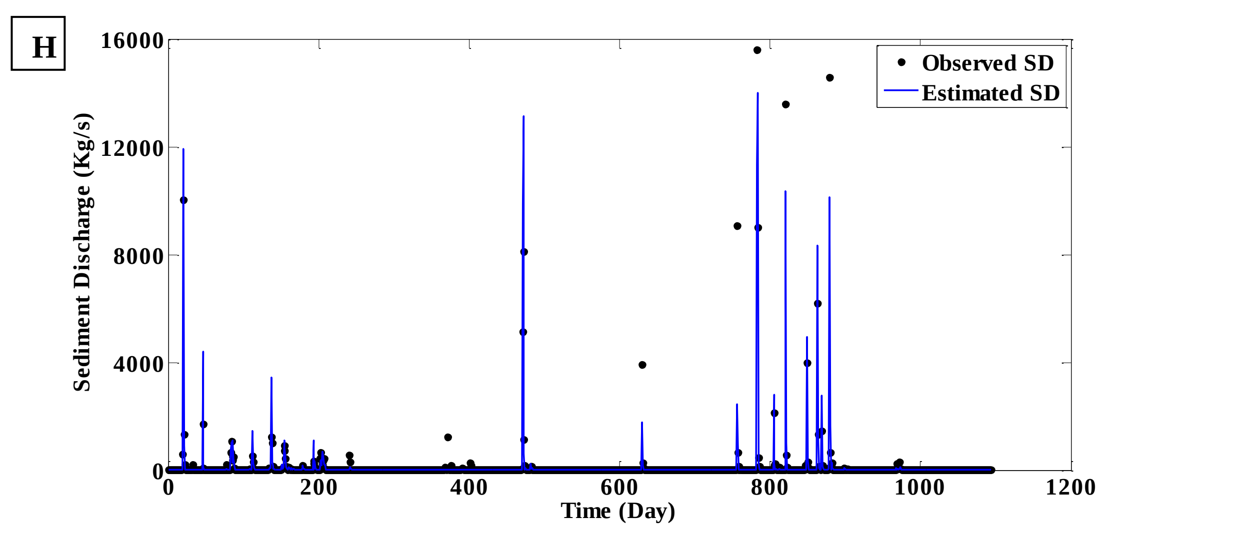

H
16000
12000
8000
4000
0
Sediment Discharge (Kg/s)
0
200
400
600
800
1000
1200
Time (Day)
Observed SD
Estimated SD

Table V-3 the improvement of the Coefficient of Determination using the Early Stopping technique.

ANNs	IMPROVEMENTS (%)
ANN 1=9	0.26
ANN 2=10	-
ANN 3=11	0.60
ANN 4=12	58.0
ANN 5=13	65.0
ANN 6=14	-
ANN 7=15	5.93
ANN 8=16	17.0

As it is shown in table V-3, six on eight networks were touched by over training, and we can say that the acceptable MLP networks ANN 1, 3, 4, 7, 8 showed improvement using Early Stopping technique the other two networks 2 and 5 are under-trained. The figure V.3 shows the training error and validation error of the ANN_4 and ANN_12 where they had the same network architecture and input combinations. We can notice that the ANN_12 improved very well using regularizing technique with improvement of 58% comparing to the non regularized Network in the first application with full iteration. The best network that was detected using cross validation was on the epoch 07, where the error of validation set had the minimum values during all epochs of the ANN_12. The over-training in this ANN started increasing from the 8^{th} epoch as it is shown in (Figure V.3). We see another important thing is that the ANN_8 and ANN_16 also had the same network architecture and input combination. The network 16 using the Early Stopping technique improved around 17% comparing to the network 8 with full iteration. We can conclude that the improvement usually occurs when we depend in the input combination on complicated data such as previous Sediment Discharge and previous Water Discharge (see ANN 12, 13, 15 and 16).

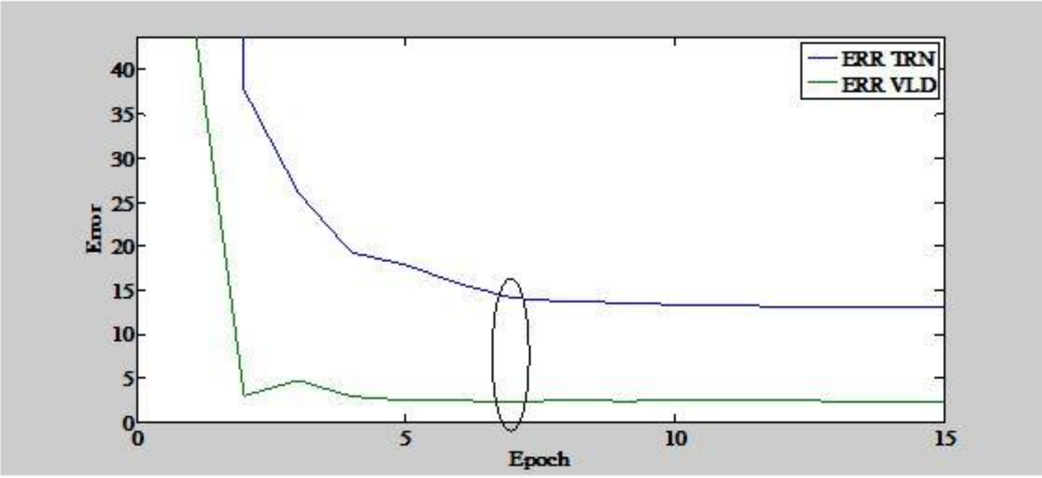


Figure V.3 The training error and validation error of the ANN 12 on the 7^{th} epoch before over-training started.

V.2 FORECASTING SUSPENDED SEDIMENT IN THE SEBAOU WADI:

To confirm the efficacy and the robustness of the developed artificial neural network models, we have predicted the suspended sediment load in the hydrometric station of Beloua (021803) which is located in the Sebaou Wadi, Great Kabyle watershed. The modelling conditions and steps we have followed are the same like the above study on the Isser Wadi, in order of ANN to compare between two different studied areas.

The data sets were comprised of water discharge (m3/s) and sediment discharge (kg/s) of period of nine years between 1^{st} September 1978 and 31^{st} August 1987. The data series were divided into three sets. We used seven years for training period (80%) from 1^{st} September 1978 to 31^{st} August 1985, and to avoid over training in the presented networks, we used 1 year (10%) for the validation set for cross-validation from 1^{st} September 1985 to 31^{st} august 1986. The last year (10%) was used to assess the performance of the model. Following the steps of the previous study we had to normalise the used data because of the different measurement units, we have applied the normalization using the same equation (1). The ranges of the normalized values of the data sets are varying from 0 to 1.

The Feed Forward Back Propagation Neural Networks that were used in this modelling, it consisted of an input layer, two hidden layers, and an output layer. The numbers of neurones in the hidden layers were varying between 3 and 15 from layer to layer and from network to network.

The performances values of the Back Propagation Neural Network were evaluated in terms of the Coefficient of Determination (R^2) and the Root Mean Square Error (RMSE). The performances values of the back propagation were tested for two different applications. In the first application, the suspended sediment load was predicted and estimated with full iterations that were given to the back propagation model to assess the best performance during training period.

In the second application the suspended sediment load was predicted using the Early Stopping technique depending on Cross Validation, which is depended on the best network during the same iterations (iterations of the simulated BPNN) to avoid over-fitting. The used input combinations were the same as used in the previous model in the case of the Isser Wadi. The performances were compared to each other for the best values of RMSE and R^2.

V.2.1 Forecasting Suspended Sediment using Non Regularized Neural Network:

Table V-4 The performances of the non regularized neural network during training, validation and testing periods depending on current and previous water discharge and previous sediment discharge.

ANN	INPUT COMBINATION	Training		Validation		Testing	
		RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_1	WD_t	0.52	98.5	4.23	87.7	1.11	68.8
ANN_2	SSD_{t-1}	3.35	06.4	3.77	06.3	0.65	06.7
ANN_3	WD_t, WD_{t-1}	0.59	97.1	1.15	90.0	0.78	75.4
ANN_4	WD_t, SSD_{t-1}	0.93	92.7	1.21	90.6	**0.61**	**77.4**
ANN_5	SSD_{t-1}, SSD_{t-2}	1.89	70.2	4.89	57.5	0.61	01.7
ANN_6	WD_t, SSD_{t-1}, SSD_{t-2}	0.37	98.9	1.67	95.7	3.74	54.7
ANN_7	WD_t, WD_{t-1}, SSD_{t-1}	**0.26**	**99.4**	1.89	81.5	5.60	16.9
ANN_8	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	0.27	99.3	**0.76**	**96.9**	1.07	76.0

The RMSE and R^2 values of the training, validation and testing period of the non regularized neural network in the Sebaou Wadi are represented in table V-4. The Back Propagation networks are trained according to the Levenberg-Marquardt algorithm with input layer, two hidden layers and output layer, with full iteration (500 epochs) for each network (8 networks).

During the training period the networks showed very good results (ANN 1, 3, 6, 7 and 8) where they learned perfectly the data that were introduced to the network with R^2 over 98%. The ANN 5 showed acceptable learning with R^2 70%, while ANN 2 showed very poor values with R^2 6.4% which means that the network didn't learn data properly and it was under-trained. In general, we say that the networks showed good learning during training period.

The correlation between input combinations and output is very high during training process in most networks, which proving the relation between the used input combinations and the output. The ANN 7 with current, previous water discharge and previous sediment discharges showed the best learning process which proves the improvement of the modelling using different current and previous water and sediment discharge as it is shown in the results of the training period. The correlation between previous sediment discharge and current sediment discharge is very low during training period but using two previous sediment discharges gave acceptable correlation during learning process between the input combination and the output.

The validation set during this application was used for cross validation to detect the best network during training period. The cross validation was used to avoid over-fitting that usually appears during ANN modelling. The performances values of the validation set gave very good values in the ANN 8, 7, 6, 4, 3 and 1 with R^2 96.9%, 81.5%, 95.7%, 90.6%, 90.0% and 87.7%, respectively. The ANN 5 and 2 showed poor performances with R^2 57.5% and 6.3% and high RMSE with (4.89 and 3.77) respectively.

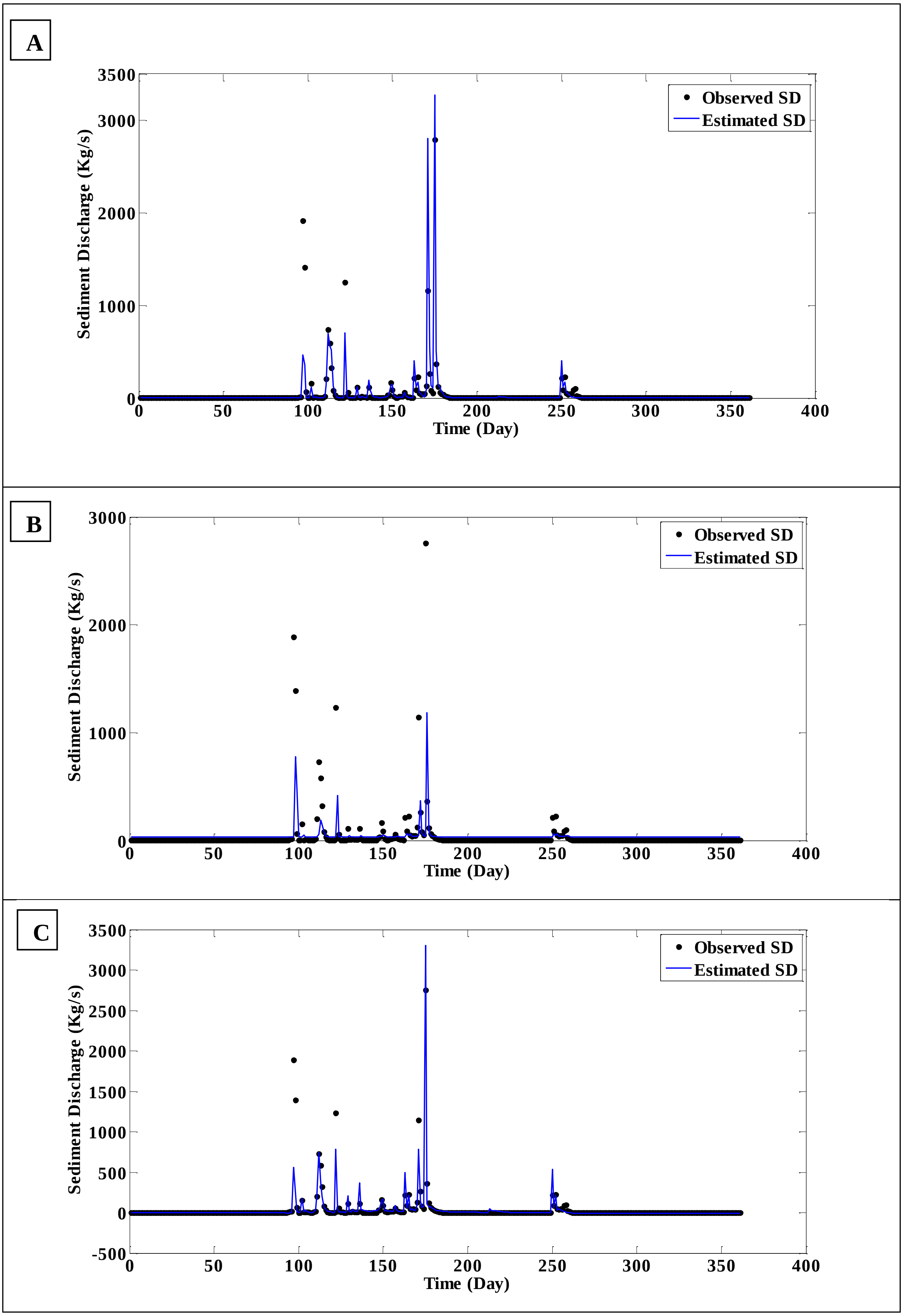
During the validation period the correlation was very strong between input combination and output, the networks 8 and 6 shows the best correlation where the results confirms the relation when depending on previous sediment discharge with current water discharge. Depending on only previous sediment discharge to estimate the current sediment discharge is very poor and antecedent sediment discharge does not correlate with current sediment discharge.

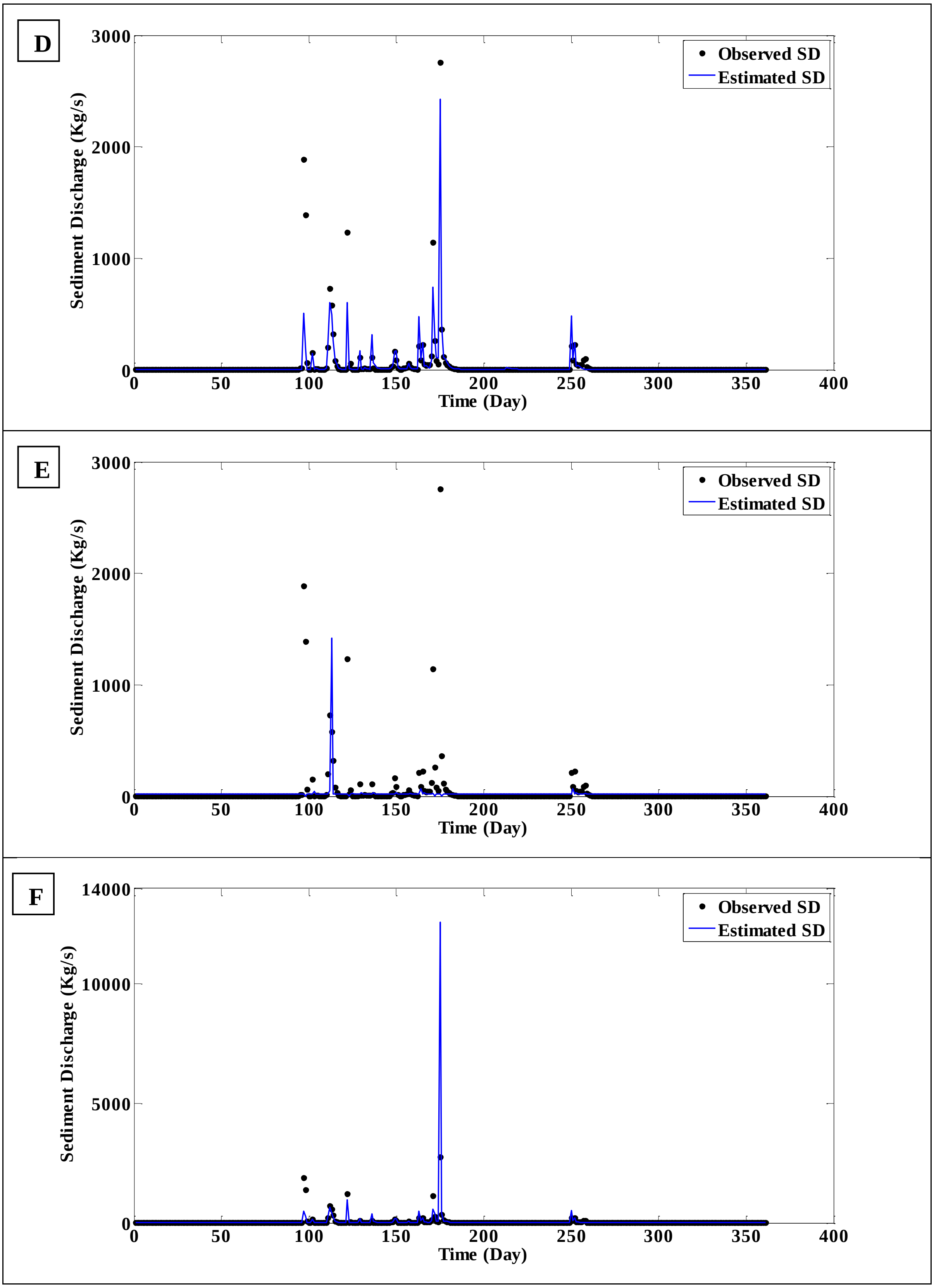
During the testing period the coefficient of determination R^2 of the ANN 8, 4 and 3 showed good values (76.0%, 77.4% and 75.4%) and with lower RMSE (1.07, 0.61 and 0.78). the ANN 1 showed acceptable values with R^2 and RMSE (68.8% and 1.11). while ANN 2, 5, 6 and 7 showed poor values with R^2 (6.7%, 1.7%, 54.7% and 16.9%) respectively.

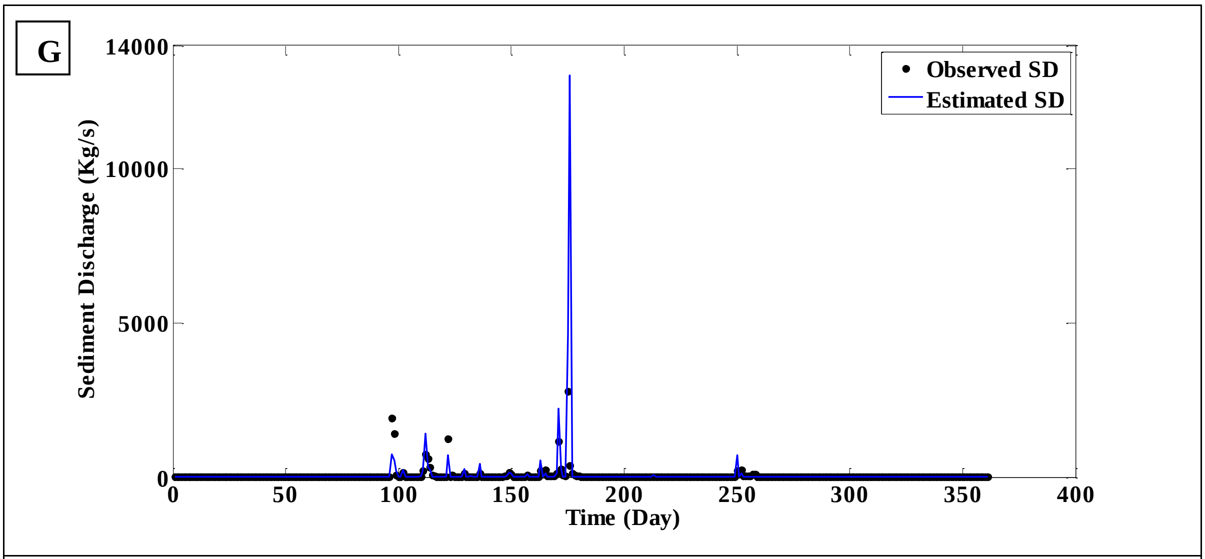
The results performance in this application using standard back propagation differ than the results that applied in the isser Wadi, where the results shows very good correlation between input combination and output in the network 4 with current water discharge and previous sediment discharge. Followed by ANN 3 with input combinations based on current and previous water discharges, and then by the network 8 with input combinations with current and previous water discharges and two previous sediment discharges.

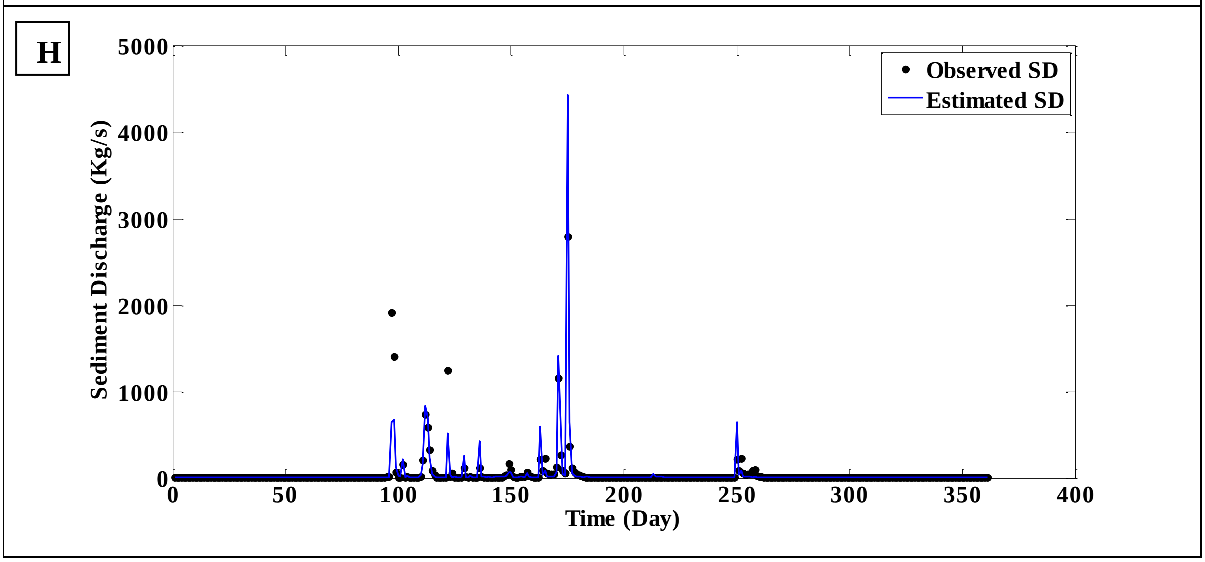
It can be said that using only previous or two previous sediment discharges as input to predict current sediment discharge is very hard because of the complexity of the phenomena and the poor correlation between input combination and the output. Contrary the other networks they showed good performance values and proved the nonlinear relation between water discharge and sediment discharge.

Figure V.4 The estimated and observed SSD using non regularized NN in the Sebaou Wadi




D
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
1000
2000
3000
0
50
100
150
200
250
300
350
400
Time (Day)
E
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
1000
2000
3000
0
50
100
150
200
250
300
350
400
Time (Day)
F
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
5000
10000
14000
0
50
100
150
200
250
300
350
400
Time (Day)


G
14000
10000
5000
0
0
50
100
150
200
250
300
350
400
Sediment Discharge (Kg/s)
Time (Day)
Observed SD
Estimated SD


H
5000
4000
3000
2000
1000
0
0
50
100
150
200
250
300
350
400
Sediment Discharge (Kg/s)
Time (Day)
Observed SD
Estimated SD

V.2.2 Forecasting Suspended Sediment using Regularized Neural Network:

Table V-5 The performances of the regularized neural networks "Early Stopping criteria's" during training, validation and testing period.

ANN	INPUT COMBINATION	Epoch	Training		Validation		Testing	
			RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_9	WD_t	06	1.21	87.7	0.54	98.8	0.67	78.1
ANN_10	SSD_{t-1}	227	3.35	06.4	3.72	40.1	0.54	04.7
ANN_11	WD_t, WD_{t-1}	47	1.09	90.0	0.92	96.4	0.82	75.9
ANN_12	WD_t, SSD_{t-1}	15	1.06	90.7	0.92	96.4	0.69	75.6
ANN_13	SSD_{t-1}, SSD_{t-2}	306	2.25	57.5	2.33	77.0	0.42	02.8
ANN_14	WD_t, SSD_{t-1}, SSD_{t-2}	54	0.72	95.7	0.60	98.5	1.03	73.8
ANN_15	WD_t, WD_{t-1}, SSD_{t-1}	24	1.49	81.5	0.77	97.5	1.79	79.0
ANN_16	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	137	**0.66**	**96.9**	**0.56**	**98.7**	**0.58**	**84.2**

Table V-5 shows the results of the training, validation and testing periods using the Early Stopping criterion based on cross validation. The networks ANN 11, 12, 14 and 16 showed very good values and pretty close to the training performances with full iterations.

It can be noticed that the chosen networks of ANN 11, 12 and 14 detected the best network early than the 60th epoch, exactly on the 47th, 15th and the 54th epochs respectively, while the ANN 16 detected the best network on the 137th epoch. The ANNs 9 and 15 showed acceptable goodness of fit with R^2 (87.7% and 81.5%) and the network were detected in the 6th and 24th epochs. The networks of the second application using the Early Stopping technique shows lower values during training period comparing to the non regularized network with full iteration (500 epoch).

The results of the learning process using the early stopping technique showed less correlation between inputs and output, explaining this weak correlation due to stopping criterion which shows the values of the network on the stopped iteration. It can be said that using only input combination depending only on sediment discharge does not give good performances because of the data complexity of the studied phenomena.

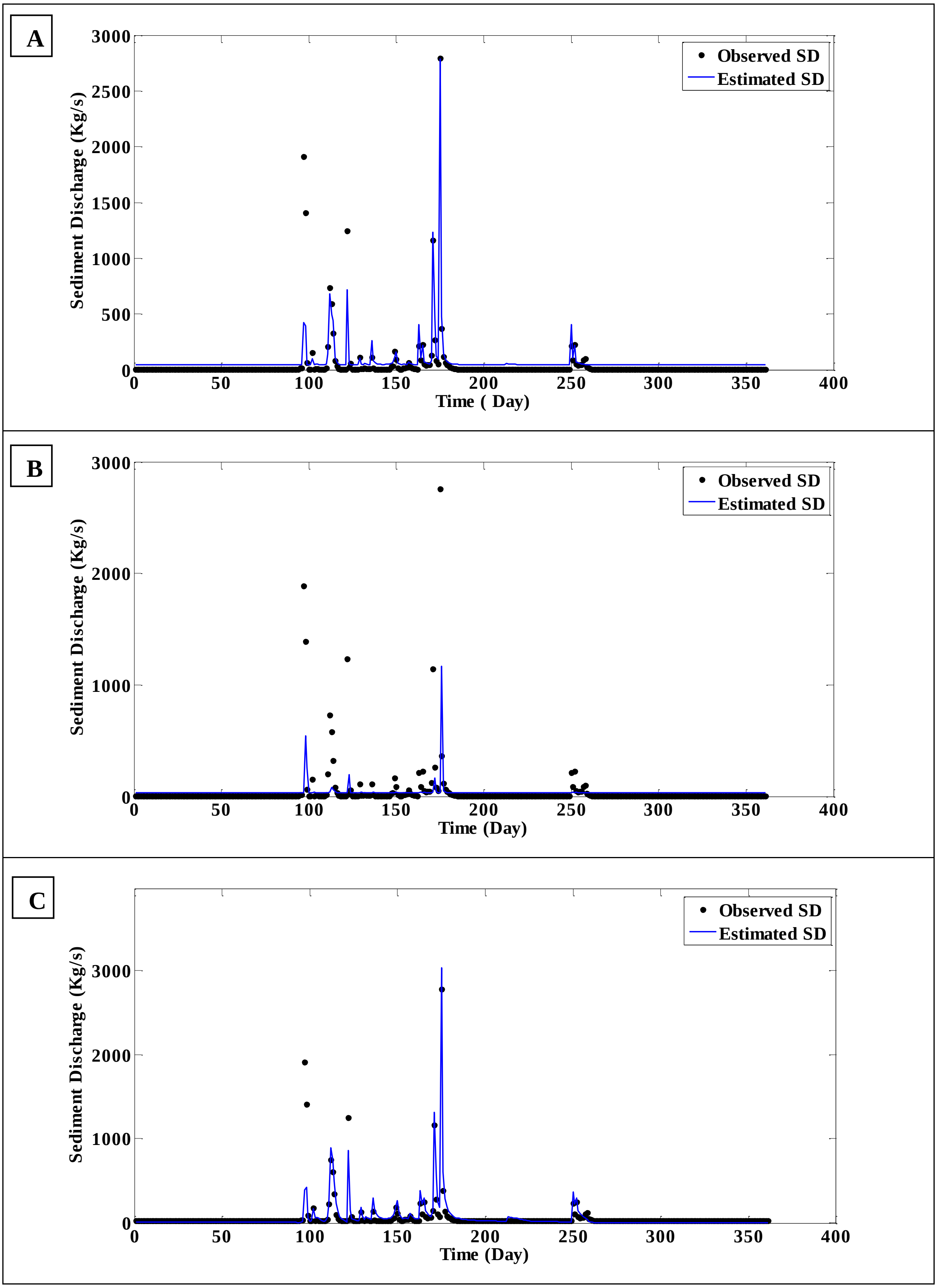
The validation period was used for cross validation to avoid over-training that usually appears in neural networks as it was explained in the above study on the Isser Wadi. The networks ANN 9, 11, 12, 14, 15 and 16 showed perfect results during this period with R^2 (98.8%, 96.4%, 96.4%, 98.5%, 97.5% and 98.7%). We can also notice that both networks with only previous and two previous sediment discharge (ANN 10 and 13) have got improved comparing to the first application with R^2 (40.1% and 77.0%).

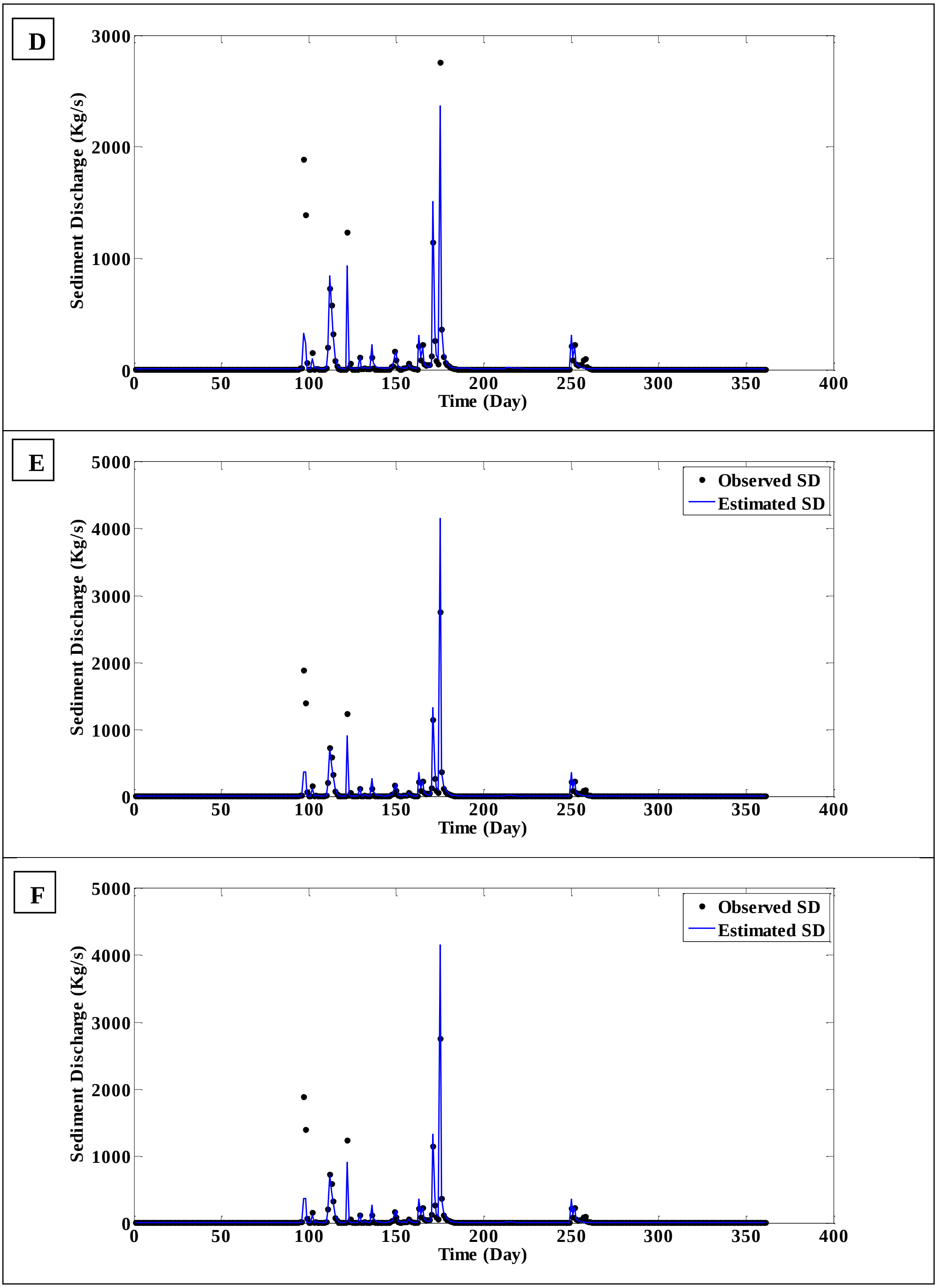
According to the results in interpretation of the connection between the used input combinations and the estimated sediment discharge during validation period, it is noticed that the correlation between inputs and output of the ANN 09, 11, 12, 14, 15 and 16 showed very high correlation. The ANN 13 depending on two previous sediment discharges gave acceptable correlation, contrary to the network 2 depending only on sediment discharge.

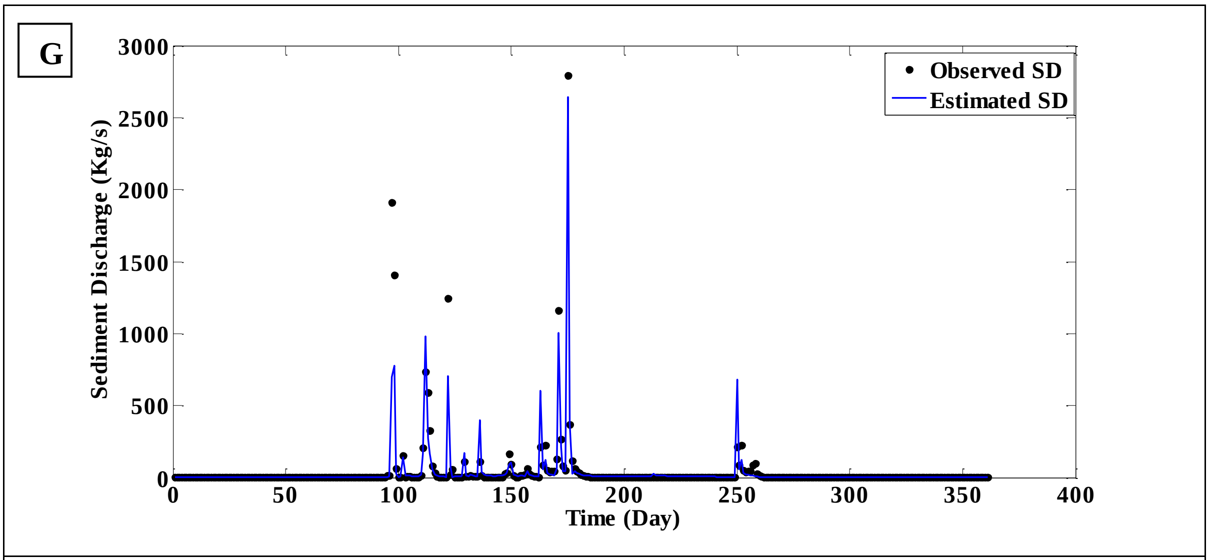
The focus of this modelling is on the testing period (table V-5) for better model evaluation. The RMSE and R^2 values of the testing period were strongly improved using the Early Stopping technique comparing to the non regularized networks. The ANN 9, 14, 15 and 16 showed very good performances and improvement with R^2 (78%, 73.8%, 79% and 84%) and RMSE (0.67, 1.03, 1.79 and 0.58). The networks 11 and 12 showed the same values like ANN 3 and 4 which means that the over fitting did not occur comparing to the other networks. The network 16 with current and previous water discharge and two previous sediment discharges gave the best performance results with RMSE 0.58 and R^2 84.2%, with an improvement by using the Early Stopping technique of 10%.

The use of current, previous water discharge and two previous values of sediment discharge as input combination have improved the prediction of sediment discharge. Comparing the results of the ANN 16 with other ANNs it can be noticed that the previous values of sediment discharge improved the performance results of the model similarly to the previous application on the Isser Wadi using the early stopping technique.

Figure V.5 The estimated and observed SSD using regularized NN in the Sebaou Wadi.




D
Sediment Discharge (Kg/s)
Time (Day)
E
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
F
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)


G
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
3000
2500
2000
1500
1000
500
0
50
100
150
200
250
300
350
400

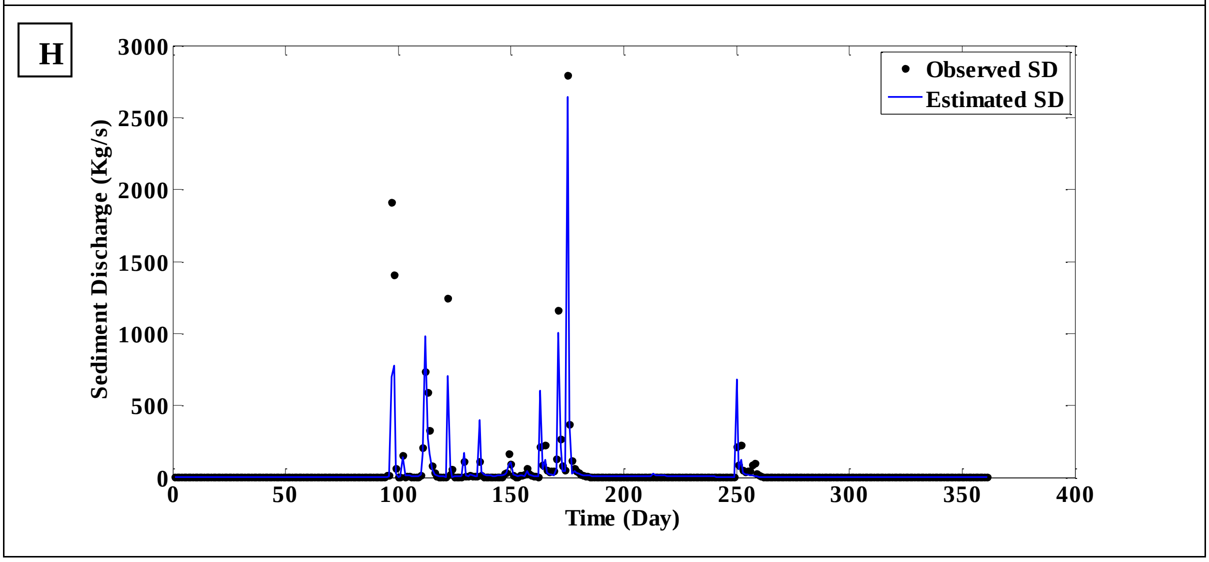

H
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
3000
2500
2000
1500
1000
500
0
50
100
150
200
250
300
350
400

Table V-6 The Neural Network improvement using the Early Stopping technique.

ANNs	IMPROVEMENTS (%)
ANN 1=9	11
ANN 2=10	-
ANN 3=11	0.7
ANN 4=12	-
ANN 5=13	39
ANN 6=14	26
ANN 7=15	79
ANN 8=16	10

As it is shown in table V-6, six on eight networks were affected by over training, and we can say that the acceptable MLP networks ANN 1, 3, 5, 6, 7, and 8 showed improvements using Early Stopping technique. The figure V-6 shows the training error and validation error of the ANN_7 and ANN_15 where they had the same network architecture and input combinations. It can be noticed that the ANN_12 improved very well using regularizing technique with improvement of 79% comparing to the non regularized network in the first application with full iteration. The best network that was detected using cross validation was in the epoch 24, where the error of validation set had the minimum values during all epochs of the ANN_15. The over-training in this ANN started increasing from the 25th epoch as it is shown in (Figure V-6). The ANN_8 and the ANN_16 also had the same network architecture and input combination. The network 16 using the Early Stopping technique was improved by around 10% on the 137th_epoch comparing to the network 8 with full iteration. It can be concluded also that usually the improvement occurs where we depend in the input combination on complicated data such as previous sediment discharge and water discharge (see ANN 9, 11, 13 and 14).

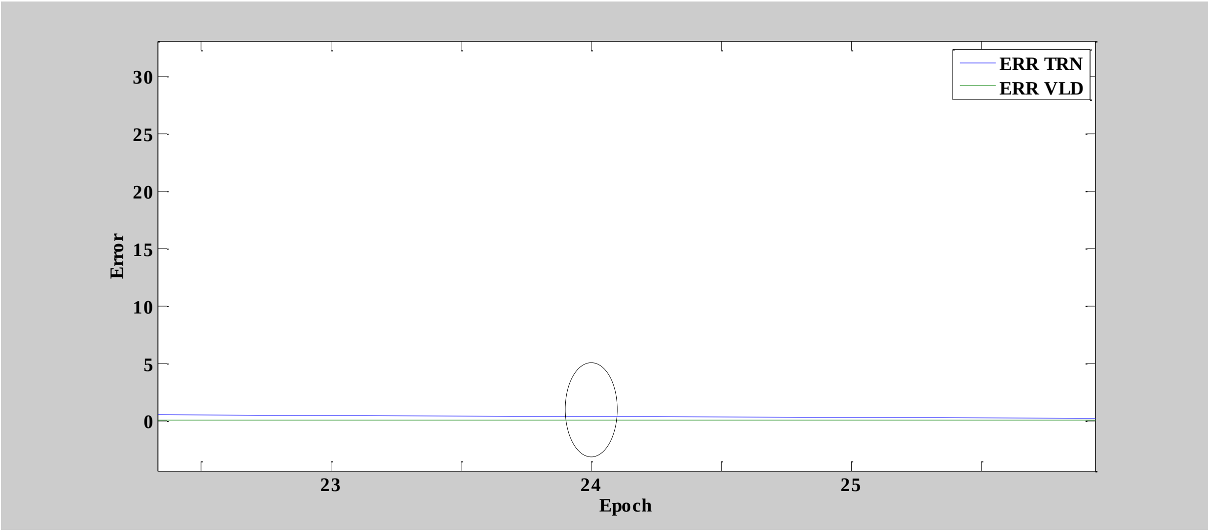


Figure V.6 The training error and validation error of the ANN 15 on the 24th epoch before over-training started.

V.3 COMPARISON OF RESULTS BETWEEN STUDIED AREAS:

For a good understanding of the Predicted Suspended Sediment Discharge and the use of ANN, we compared the performance results and input combinations of the different used studied areas under same climatic factors and geological structures of both areas, taking under consideration the different modelled periods.

It can be seen that during testing period the performance results of the Isser Wadi gave better results of the networks ANN, 1 with current water discharge, ANN 3 with current and previous water discharge, and ANN 7 with current, previous water discharge and previous sediment discharge than the Sebaou Wadi. Contrary, the ANN 4 with current water discharge and previous sediment discharge, ANN 6 with current water discharge and two previous sediment discharge, and ANN 8 with current and previous water discharge and two previous sediment discharges, they indicated better results than the networks of the Issser Wadi. In both studied areas using non regularized neural network, the ANN 3 of the application in the Isser Wadi gave the best performance values. In the application of the Sebaou Wadi, the ANN 4 gave the best performance values.

As far as the regularized neural network using the Early Stopping technique, is considered clearly that the results of the training and validation period of the Sebaou

Wadi are better than the results of the Isser Wadi. We can explain this priority of the performance results to the Sebaou Wadi because of the difference periods of the introduced data for both models. We used input data of twenty four years for the Isser Wadi, while only seven years for the Sebaou Wadi.

In the testing period of the Isser Wadi we can see that the networks ANN 11 with current and previous water discharge, and ANN 15 with current and previous water discharge and previous sediment discharge showed better results than the Sebaou Wadi. On the other side, the ANN 9 with current water discharge, ANN 12 with current water discharge and previous sediment discharge, and ANN 16 with current and previous water discharge and two previous sediment discharge of the Sebaou Wadi gave better values than the same ANNs of the Isser Wadi.

In order to compare between the improved neural networks depending on the corss validation technique, we take under comparison only the networks that indicated good performance values during testing period. The improvement of the ANN 12 and 16 of the Isser Wadi were better than the Sebaou Wadi, and the ANN 9, 11, 14 and 15 were better for the Sebaou application, and the highest improvement of ANN 15 in the Sebaou Wadi 79%.

It is obvious that the improvement percentage of the coefficient of determination using the regularized neural network reacted better in the Sebaou Wadi than the Isser Wadi. We can clearly conclude that the use of regularized neural network improved the prediction of suspended sediment discharge in both rivers with priority of the higher results to the Sebaou Wadi. We can also say that the input combination depending on current water discharge and different previous sediment discharge gave better results for the Sebaou Wadi, contrary to the model of the Isser Wadi where the performance values of the input combination depending on the current and previous water discharge were better than the other networks.

V.4 FORECASTING SUSPENDED SEDIMENT IN UNGAUGED WATERSHED:

To improve the ability of predicting the suspended sediment load in rivers and to develop new and innovative models using ANN in ungauged catchments, we tried to predict sediment discharge in both Isser and Sebaou Wadis, depending on data of each other's and we applied both regularized and non regularized neural networks on both models.

The both studied areas are neighbours to each other, and sharing the same climatically factors and characteristics, both valleys pouring into the Mediterranean Sea. However, there are some differences in the hydrological and hydro-geological parameters between studied areas.

V.4.1 Forecasting Suspended Sediment of the Sebaou Wadi using the input data during training period of the Isser Wadi:

In general, training, validation and testing are the fundamental steps for neural network process. We used the input data from the Lakhdaria hydrometric station in the Isser watershed for the training data during a period of 14 years between 1st Sep 1971 and 31st August 1985 to predict the suspended sediment discharge in the Sebaou Wadi, Great Kabyle watershed. The validation set was used for cross validation to avoid over-training in the networks. The validation set used comes from the hydrometric station of Beloua (021803) in the Sebaou Wadi. The data used for cross validation were from a period of 1 year between 1st Sep 1985 and 31st August 1986. The testing set was used from the Belloua hydrometric station as well, during period of 1 year from 1 Sep 1986 to 31 August 1987. The performance of the Back Propagation model was tested for two different applications. In the first application, the suspended sediment load was predicted and estimated with full iteration that was given to the back propagation model. In the second application the suspended sediment load was predicted using the Early Stopping technique which avoids the over-training that occurs often during training period.

V.4.1.1 Forecasting Suspended Sediment using Non Regularized Neural Network:

Table V-7 The performances of the non regularized neural network during training, validation and testing periods depending on current and previous water discharge and previous sediment discharge.

ANN	INPUT COMBINATION	Training		Validation		Testing	
		RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_1	WD_t	6.68	58.1	3.68	13.0	**3.51**	**78.7**
ANN_2	SSD_{t-1}	8.35	33.2	3.67	12.4	1.11	09.2
ANN_3	WD_t, WD_{t-1}	5.50	69.9	2.90	45.5	1.50	49.0
ANN_4	WD_t, SSD_{t-1}	5.71	68.9	1.24	90.0	4.45	68.3
ANN_5	SSD_{t-1}, SSD_{t-2}	7.62	43.7	3.58	17.0	1.47	09.4
ANN_6	WD_t, SSD_{t-1}, SSD_{t-2}	4.46	80.8	1.54	84.5	4.76	41.5
ANN_7	WD_t, WD_{t-1}, SSD_{t-1}	**2.98**	**91.5**	2.06	72.4	3.62	34.5
ANN_8	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	4.16	83.3	**1.11**	**92.0**	3.64	73.2

The RMSE and R^2 values of the training, validation and testing period of the non regularized networks are represented in table.V-7, the Back Propagation neural networks were trained according to the Levenberg-Marquardt algorithm, with an input layer, two hidden layers and output layer with full iteration (200 epoch) for each network (8 networks).

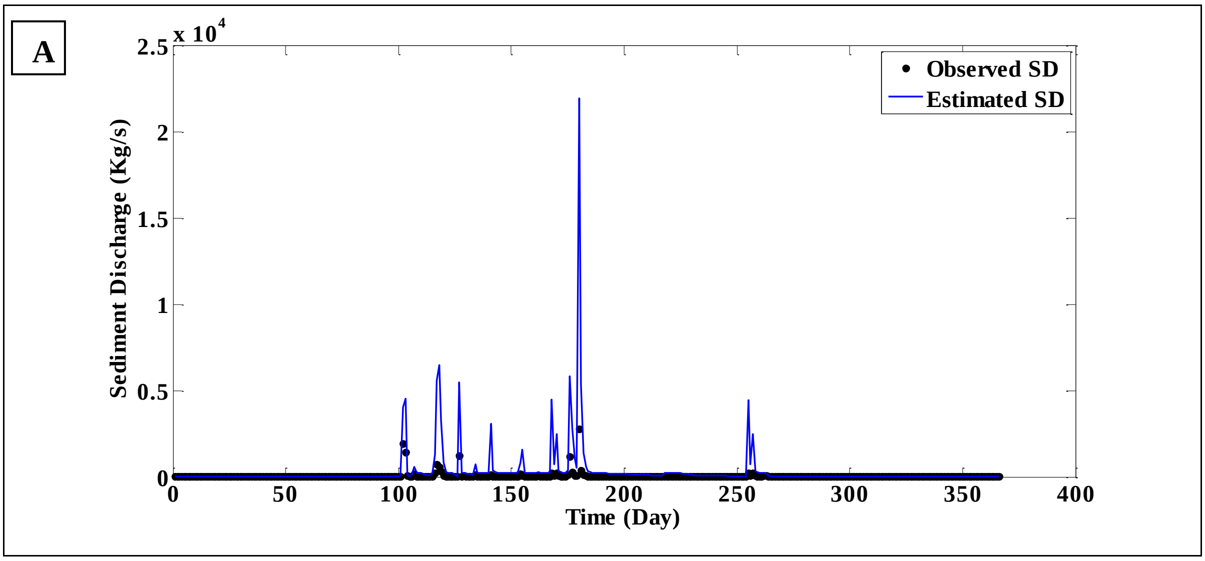
The performances values of the training period showed acceptable results on the ANN 6, 7 and 8 with R^2 (80.8%, 91.5% and 83.32%). And average R^2 values for ANN 3 and 4 with (69.9% and 68.9%) and the rest of ANN showed poor learning during training period due to the complexity of the suspended sediment data. The input combinations of the best ANNs during training period are depending on both values of water discharge and sediment discharge together.

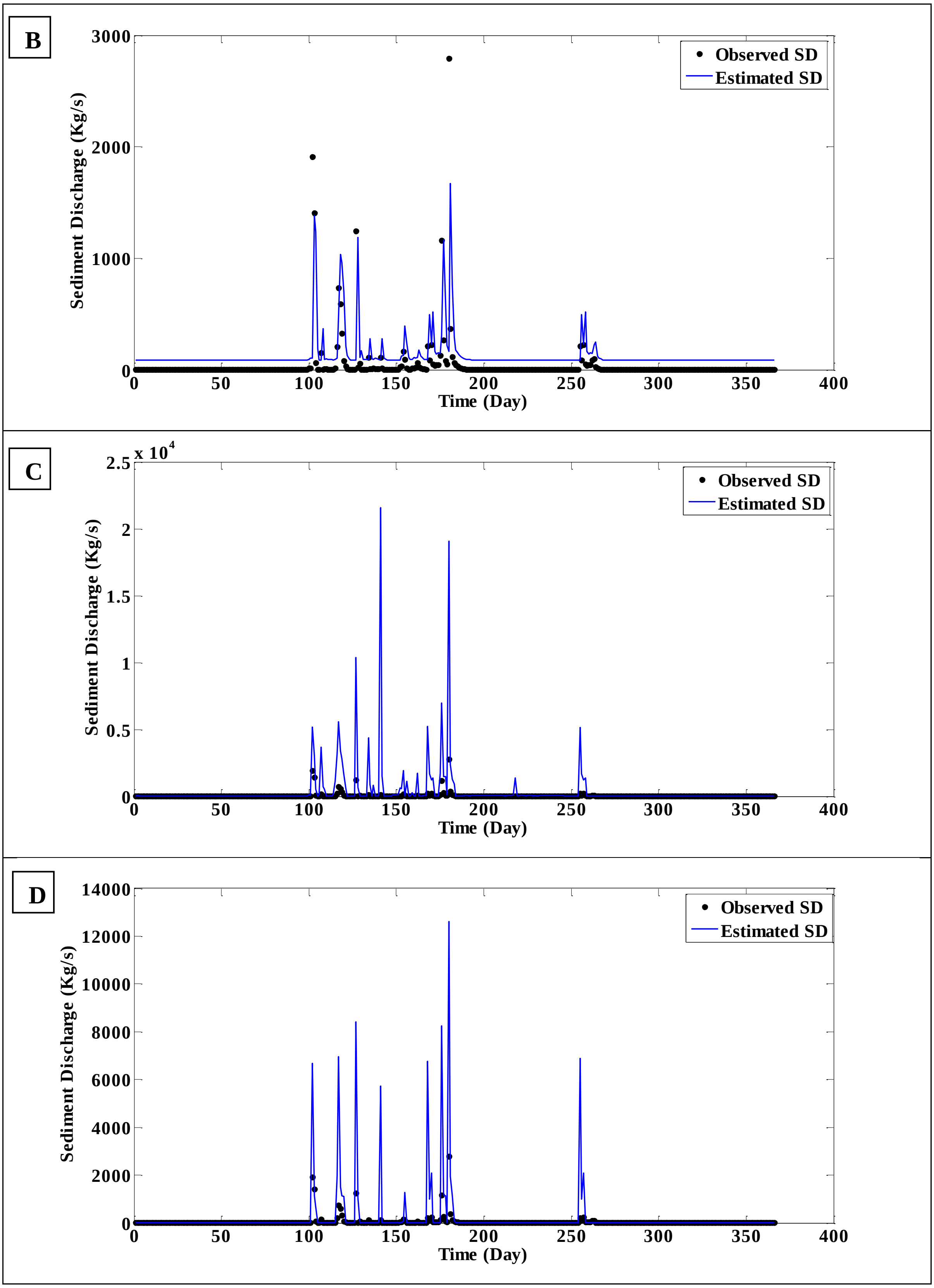
The validation set was used for cross validation to avoid over-training. The performances values of this period showed good results in ANN 4, 6, 7 and 8 with R^2 (90.0%, 84.5%, 72.4% and 92%) respectively. The best used combination of the networks during validation period are the inputs depending on both water discharge and sediment discharge which means the strong relationship between inputs depending on both variables with the predicted sediment discharge.

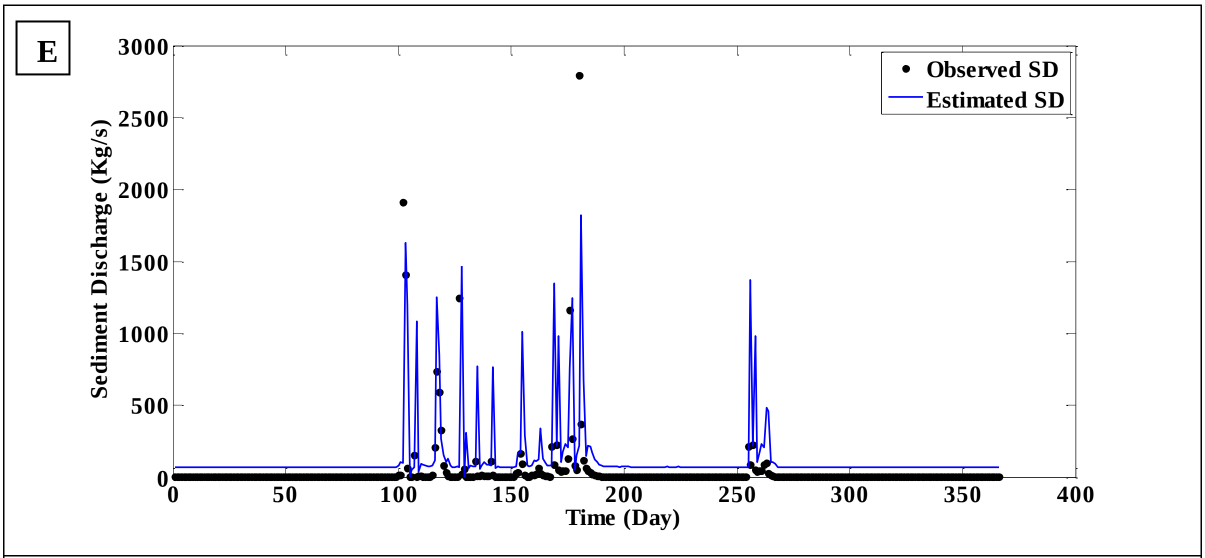
The models evaluation RMSE and R^2 during testing period of the non regularized networks (full iteration) and depending on training inputs from another area, shows the best results in this application in the network with current water discharge ANN 1 with R^2 78.7% and RMSE 3.51. The ANN 4 and 8 showed average values with R^2 68.3% and 73.2%. The ANN 2, 3, 5, 6 and 7 showed poor values during this period. It can be seen that the R^2 were good in ANN 1, 4 and 8 which means the goodness of fit of the simulated values is good, but the RMSE of the same models were poor, we explain this phenomenon due to under-training and to the complexity of the data.

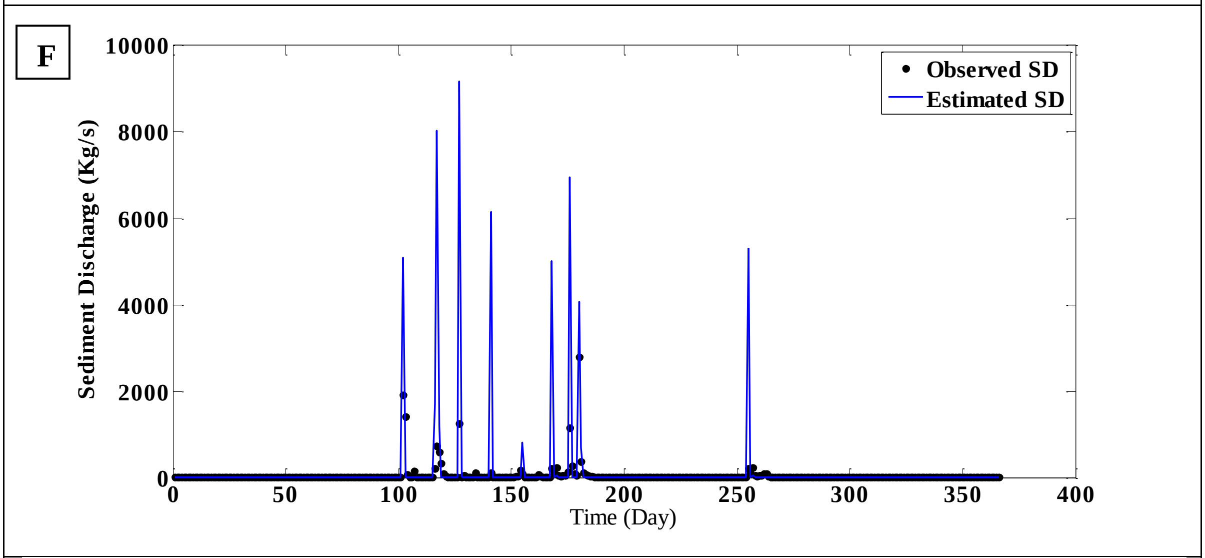
The ANNs 1 and 3 both depending only on water discharges values gave good relationship with predicted sediment discharge during the testing period. However, the predicted sediment discharge using data from nearby Wadi did not give satisfying performances values comparing to the results of gauged catchment.

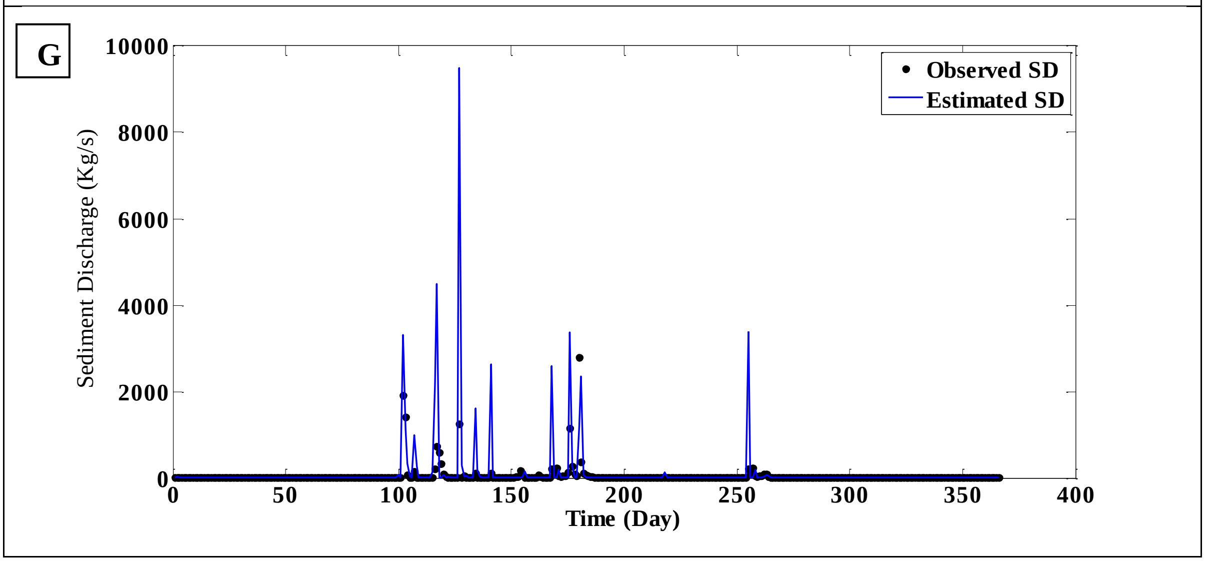
Figure V.7 The estimated and observed SSD using non regularized NN in the ungauged Sebaou.

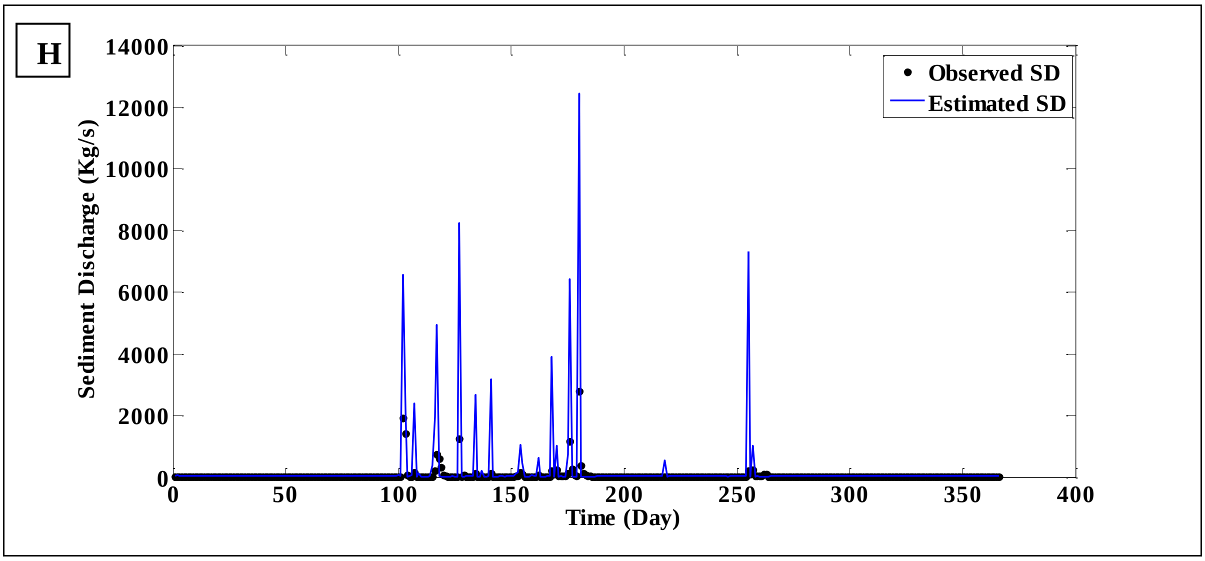



B
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
3000
2000
1000
0
0
50
100
150
200
250
300
350
400
Time (Day)
C
x 10^4
2.5
2
1.5
1
0.5
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
D
14000
12000
10000
8000
6000
4000
2000
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)


E
3000
2500
2000
1500
1000
500
0
Sediment Discharge (Kg/s)
0
50
100
150
200
250
300
350
400
Time (Day)
Observed SD
Estimated SD


F
10000
8000
6000
4000
2000
0
Sediment Discharge (Kg/s)
0
50
100
150
200
250
300
350
400
Time (Day)
Observed SD
Estimated SD


G
10000
8000
6000
4000
2000
0
Sediment Discharge (Kg/s)
0
50
100
150
200
250
300
350
400
Time (Day)
Observed SD
Estimated SD



V.4.1.2 *Forecasting Suspended Sediment Discharge using Regularized Neural Network:*

Table V-8 The performances of the regularized networks "Early Stopping criteria's" during training, validation and testing period.

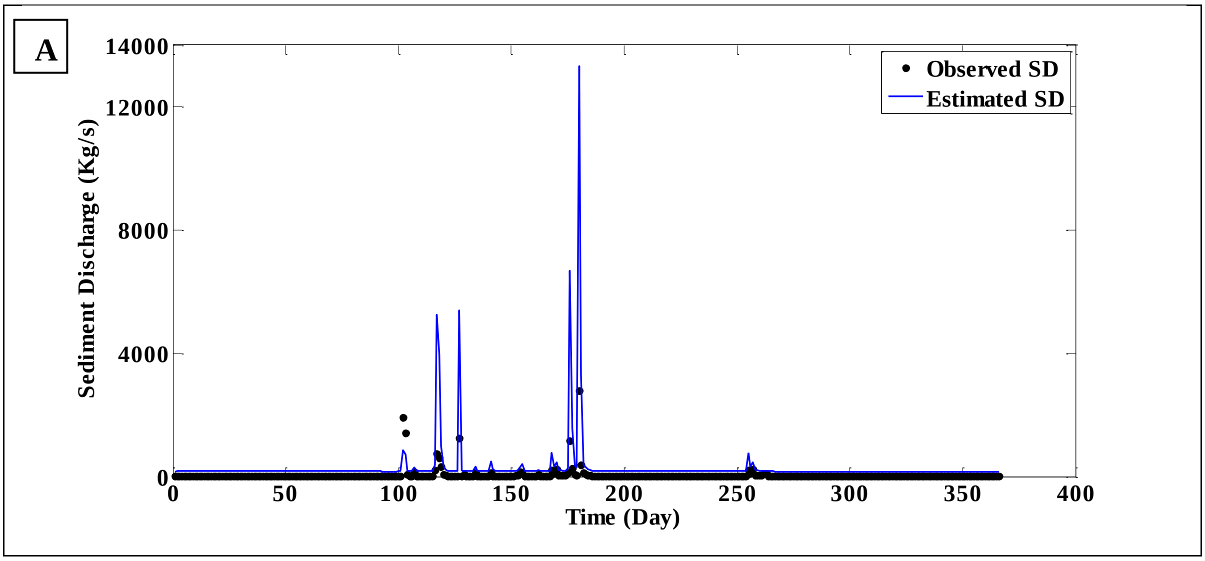
ANN	INPUT COMBINATION	Epoch	Training		Validation		Testing	
			RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_9	WD_t	05	8.21	50.8	0.30	88.5	0.82	69.8
ANN_10	SSD_{t-1}	36	8.35	32.5	3.52	19.2	0.91	07.2
ANN_11	WD_t, WD_{t-1}	08	6.47	59.1	8.35	05.3	3.73	70.0
ANN_12	WD_t, SSD_{t-1}	08	6.82	54.3	1.74	80.3	**3.00**	**70.7**
ANN_13	SSD_{t-1}, SSD_{t-2}	19	8.21	34.6	3.34	27.2	0.90	07.4
ANN_14	WD_t, SSD_{t-1}, SSD_{t-2}	03	7.15	51.5	**0.89**	**94.8**	1.96	62.9
ANN_15	WD_t, WD_{t-1}, SSD_{t-1}	06	**4.82**	**77.4**	1.15	91.4	3.53	70.1
ANN_16	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	09	8.50	29.4	1.27	89.6	0.25	75.7

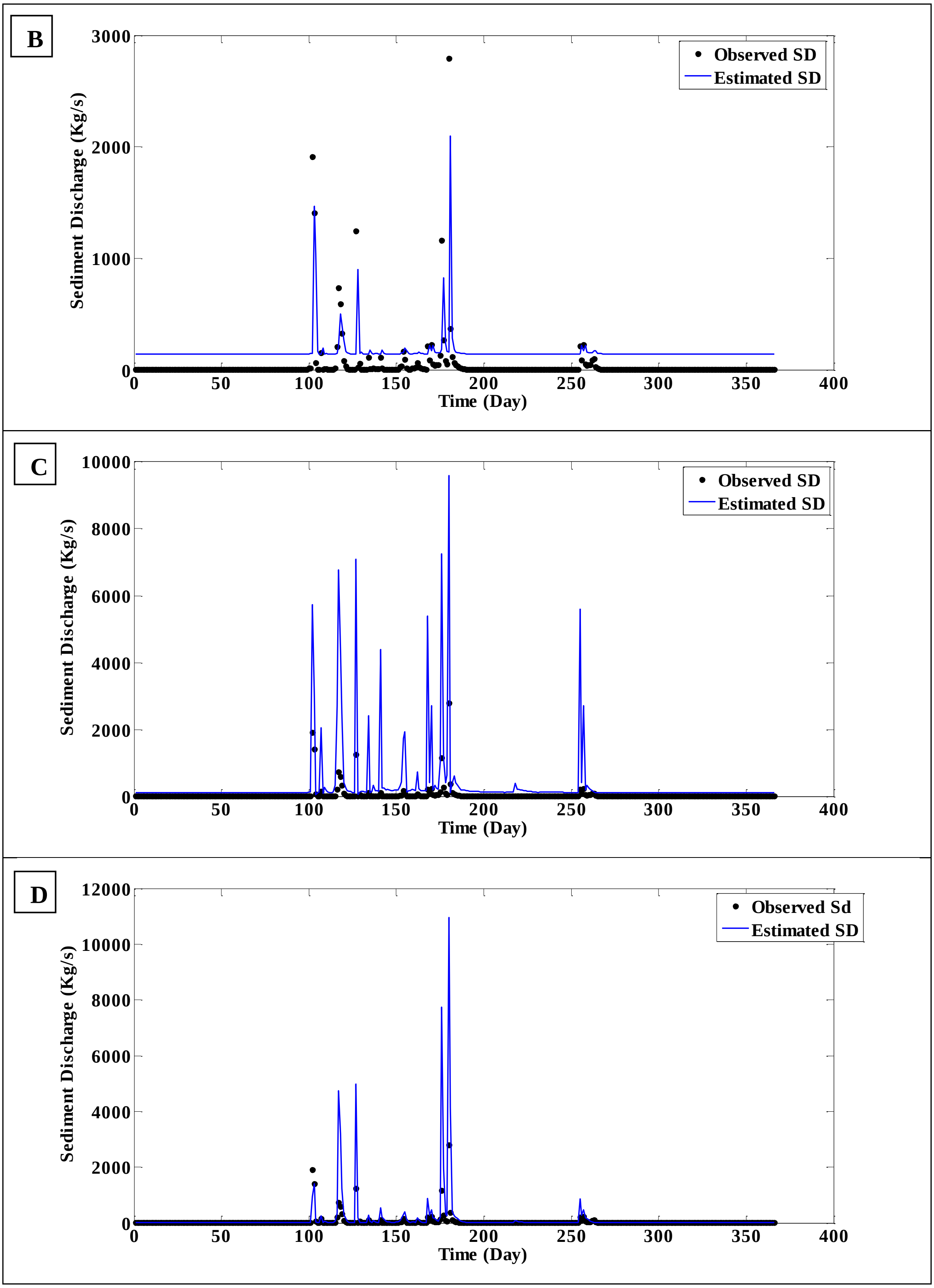
Table V-8 represents the RMSE and R^2 during training, validation and testing periods. The performances values of these applications show the best networks using the Early Stopping technique. The training period of the ungauged watershed shows very poor results comparing to the previous gauged applications of Sebaou and Isser. The best R^2 in both regularized and non regularized neural networks showed that ANN 15 with 77.4% and RMSE with 4.82 gave the best performance results. Poor values were obtained because of depending during cross validation on data from a different hydrometric station than the data were used for training period.

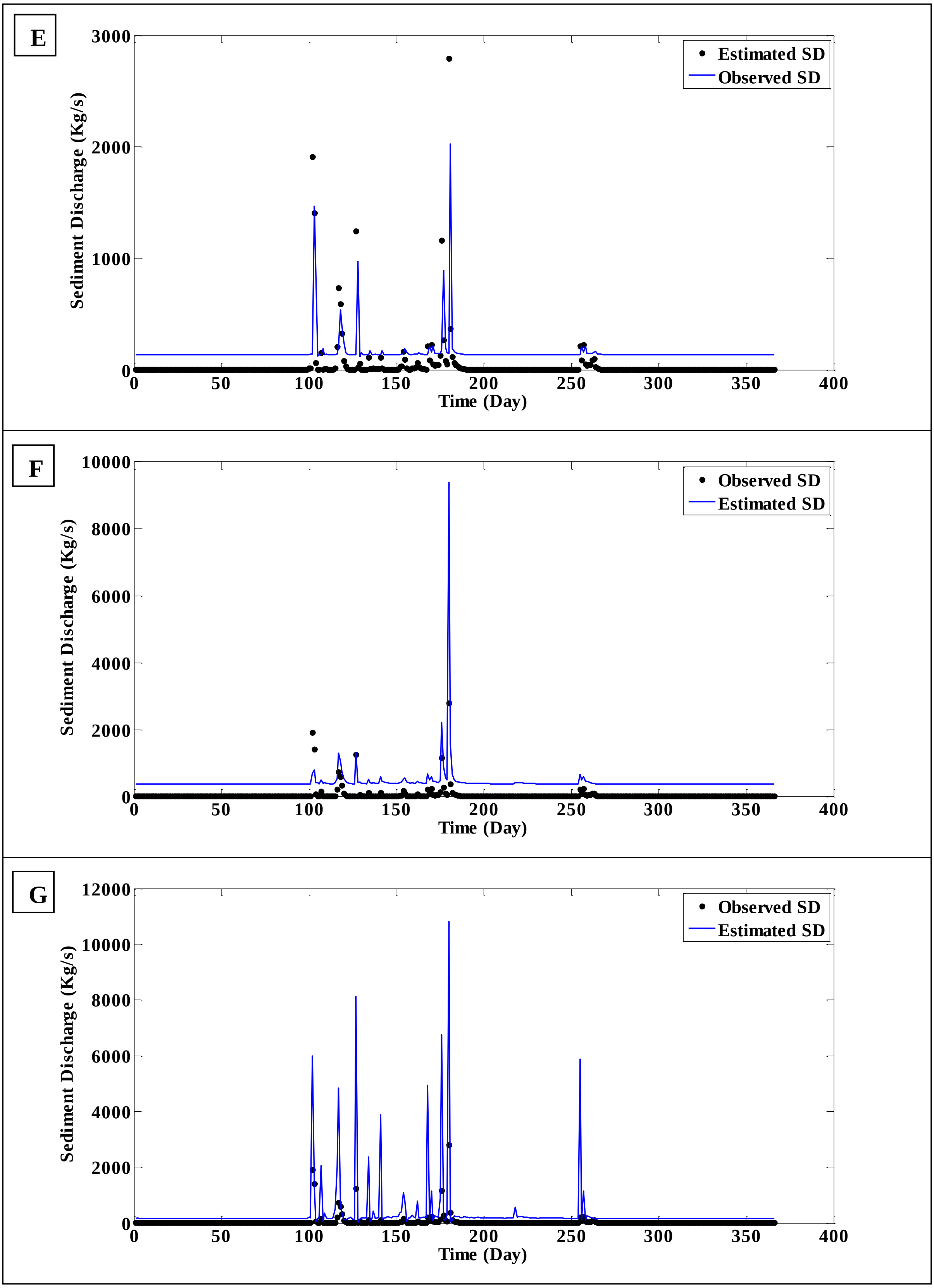
Contrary to the poor performances values of the training data, the validation period showed very good values, the ANN 1, 4, 6, 7 and 8 showed very good results with RMSE (0.30, 1.74, 0.89, 1.15 and 1.72), and R^2 with (88.5%, 80.3%, 94.8%, 91.4% and 89.6%) and it can be noticed that the ANN 14 with current water discharge and two previous sediment discharge showed the best results. The results during the validation set are the best due to the network best obtained error according the validation section.

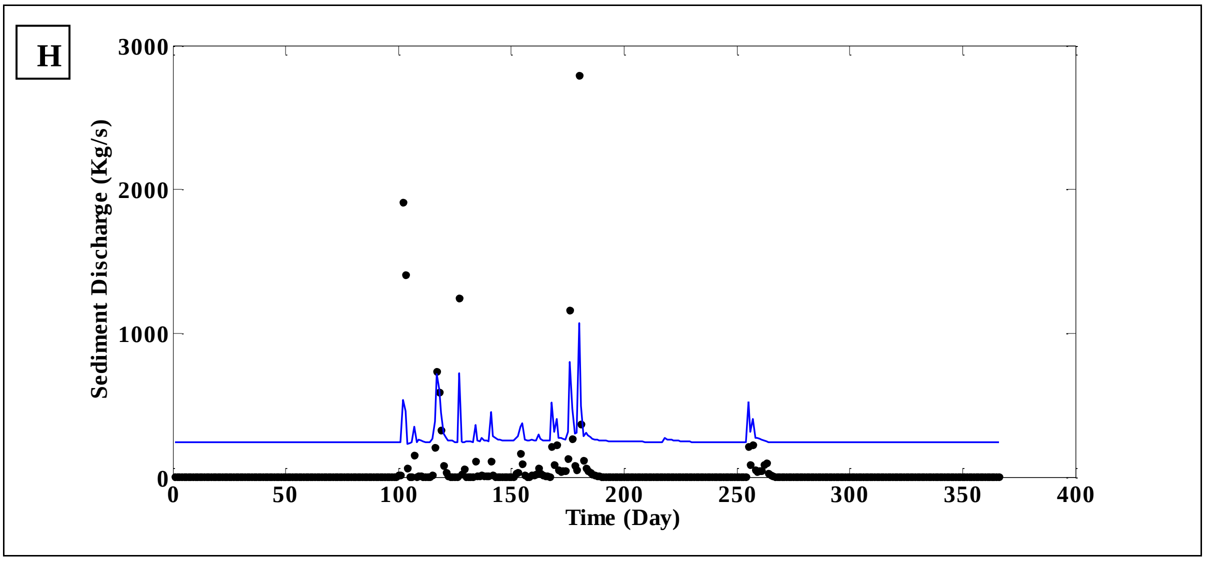
During the testing period the networks improved comparing to the non regularized neural networks in the previous application. We can say that the networks gave acceptable values for the ANN 11, 12 and 15 with R^2 (70%, 70.7% and 70.1%) and RMSE with (3.73, 3.00 and 3.53) we can notice that most of ANNs gave good R^2 between 62% and 76%, which means that the estimated values showed acceptable goodness of fit, but still the RMSE showing poor results. It can be noticed from figures bellow (Figure V.8) that most networks showed acceptable R^2 and poor results of RMSE, they had over-estimation of the observed values. The most effective input combination in this application using the early stopping technique was depending on both current water discharge and previous sediment discharge.

Figure V.8 The estimated and observed SSD using regularized NN in the ungauged Sebaou.




B
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
C
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
D
Observed Sd
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)


E
Estimated SD
Observed SD
Sediment Discharge (Kg/s)
Time (Day)
F
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
G
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)



In order of comparing this part where we used input data from Isser Wadi to predict sediment in Sebaou Wadi. The RMSE and R^2 during testing period of the regularized neural networks showed better values where we used training, validation and testing data of Belloua hydrometric station, comparing the results where we used the training input data of the Isser Wadi Lakhdaria hydrometric station. We can see clearly that ANN 1 depedning on the input data of the Isser showed better fit than using input data of the Sebaou but still higher RMSE, which means that the neural network used data of the same region are better. It can be said also that depending on water discharge of closed area can be used and dependable in some cases.

Table V-9 The comparison of the testing period of the Sebaou performance values, once using input training of the Sebaou and secondly using input training of the Isser.

ANNs	R^2 (inputs of the Sebaou)	R^2 (inputs of the Isser)
Ann 01	68.8	78.7
Ann 08	76.0	73.2
Ann 09	78.1	69.8
Ann 11	75.9	70.0
Ann 12	75.6	70.7
Ann 14	73.8	62.9
Ann 15	79.0	70.1
Ann 16	84.2	75.7

It can be noticed in table V-9 that the values of the coefficient of determination (R^2) of the Sebaou Wadi depending on the data from the Isser Wadi showed acceptable goodness of fit, and close to the performance values depending on the same watershed data (Sebaou Wadi), which means that the obtained neural network model can be improved in the use of prediction in ungauged basin with the same climatic characteristics.

V.4.2 Estimating Suspended Sediment Discharge of the Isser Wadi using the input data of the Sebaou Wadi for training period:

V.4.2.1 Forecasting Suspended Sediment using Non Regularized Neural Network:

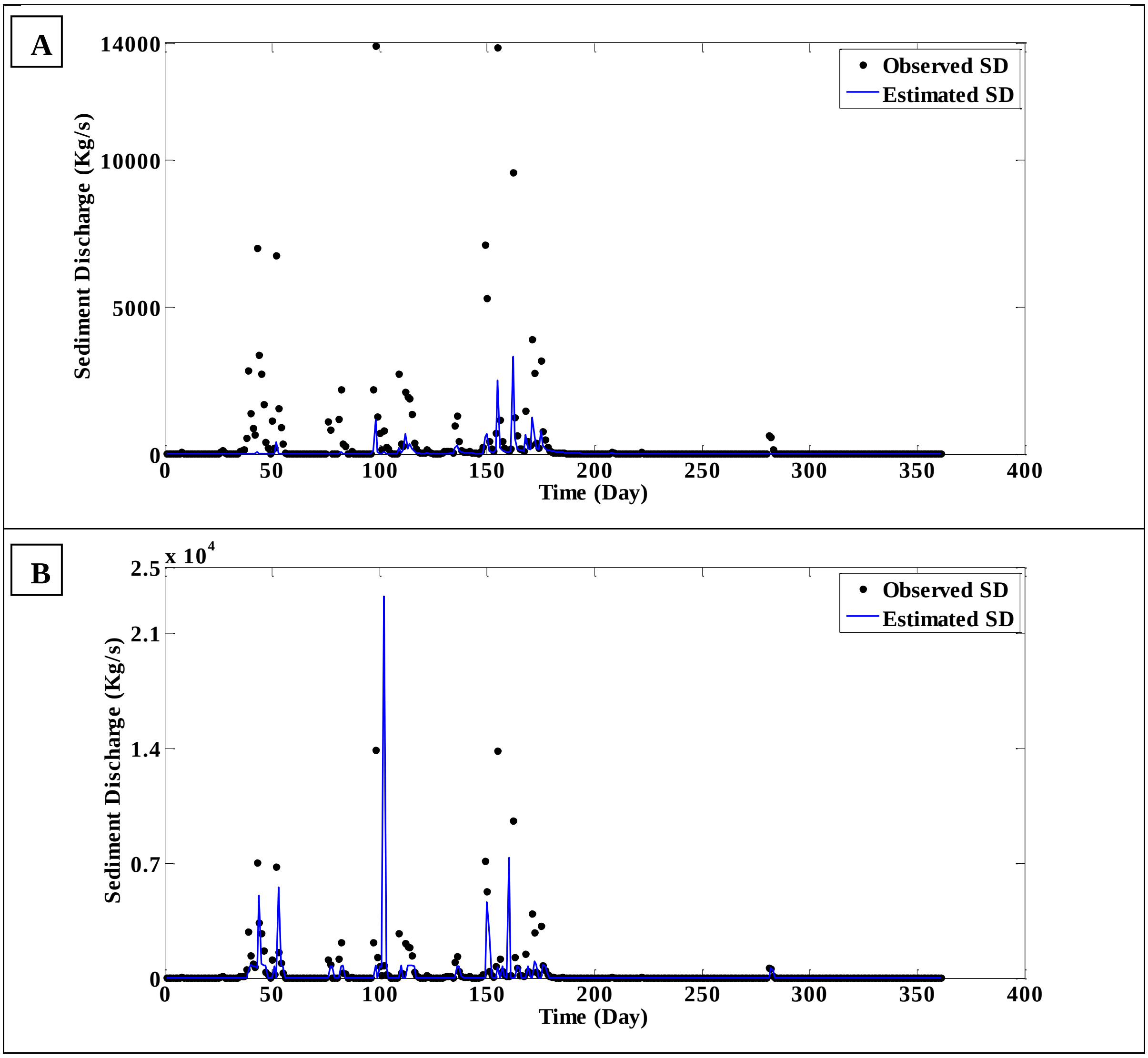
Table V-10 The performances of the non regularized neural network during training, validation and testing periods depending on current and previous water discharges and previous sediment discharges.

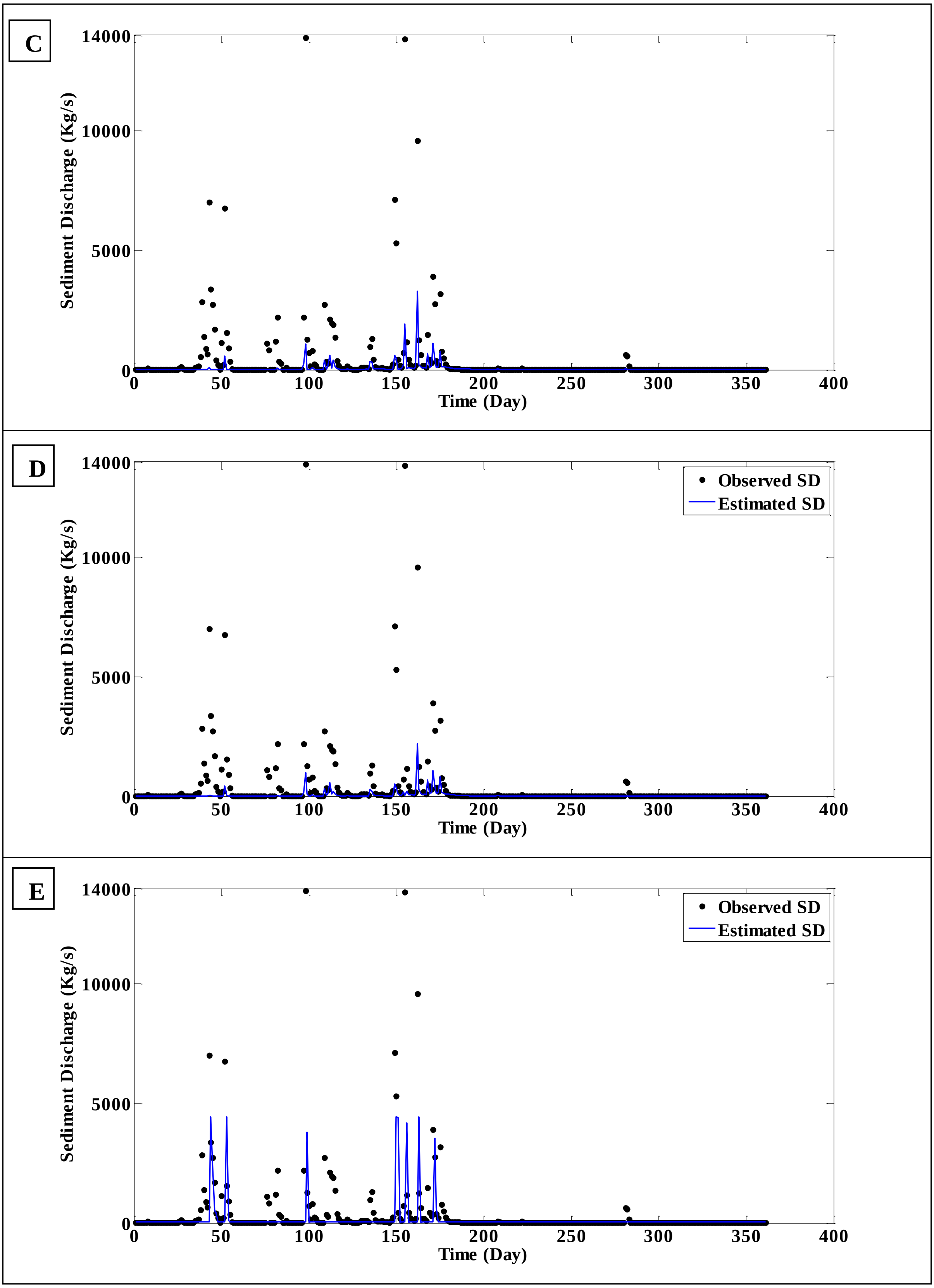
ANN	INPUT COMBINATION	Training		Validation		Testing	
		RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_1	WD_t	0.53	96.5	06.69	63.3	**0.81**	**62.9**
ANN_2	SSD_{t-1}	2.09	46.0	10.93	01.0	7.23	01.7
ANN_3	WD_t, WD_{t-1}	0.43	97.7	**06.23**	**68.1**	0.76	61.3
ANN_4	WD_t, SSD_{t-1}	0.30	98.9	09.85	19.5	0.64	42.0
ANN_5	SSD_{t-1}, SSD_{t-2}	1.59	68.6	10.29	11.3	3.23	04.2
ANN_6	WD_t, SSD_{t-1}, SSD_{t-2}	0.33	98.7	10.44	09.4	5.98	00.7
ANN_7	WD_t, WD_{t-1}, SSD_{t-1}	0.38	98.2	10.07	15.9	0.74	33.9
ANN_8	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	**0.18**	**99.6**	10.72	04.9	0.55	31.4

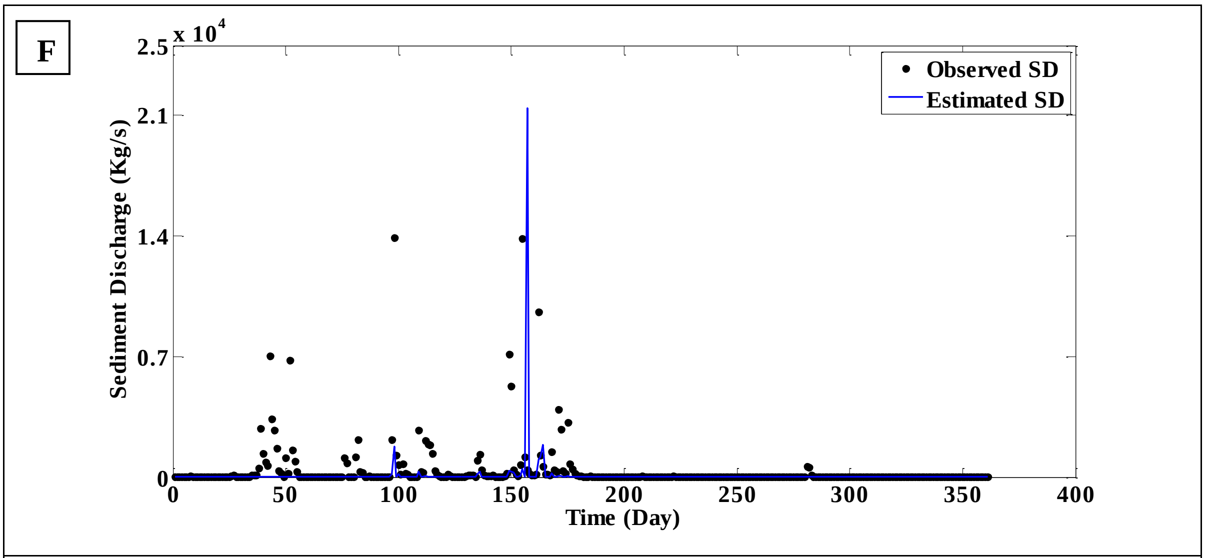
Table V-10 represents the RMSE and R^2 performances values of the training, validation and testing period of the non regularized neural networks. The used inputs for training set in this application come from the hydrometric station of Belloua, in the Great Kabyle watershed to predict sediment discharge of the Lakhdaria hydrometric station, in the Isser Wadi.

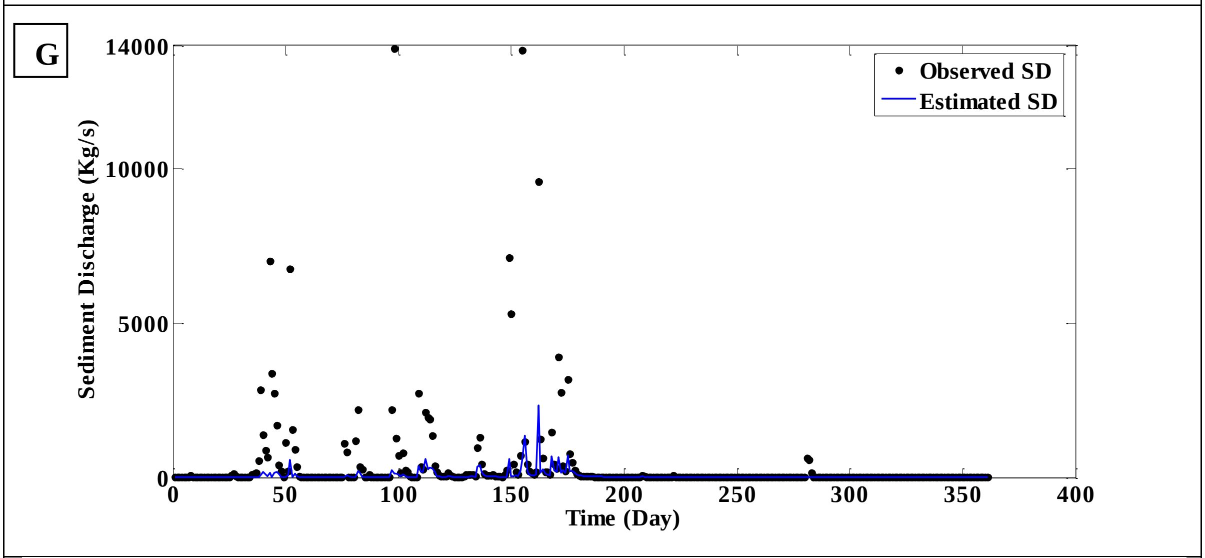
In the training period using the non regularized neural network showed that R^2 were over 96% in ANNs 1, 3, 4, 6, 7 and 8. The RMSE and R^2 of the validation period showed very poor values with highest R^2 of the ANN 3 with (68.1%). Because of different training input data that was given to the neural networks, the testing period showed poor values as in the validation set. The ANN 1 showed the best coefficient of determination with R^2 62.9%.

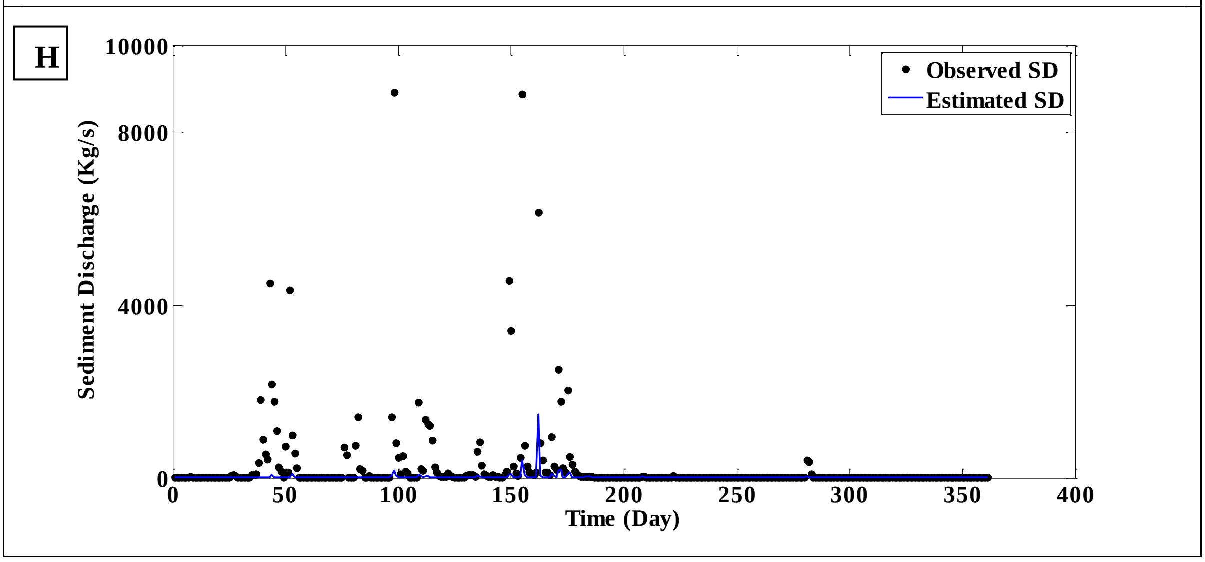
Figure V.9 The estimated and observed SSD using non regularized NN in ungauged Isser.




C
Sediment Discharge (Kg/s)
14000
10000
5000
0
0 50 100 150 200 250 300 350 400
Time (Day)
D
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)
E
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
Time (Day)


F
x 10^4
Sediment Discharge (Kg/s)
Time (Day)
Observed SD
Estimated SD


G
Sediment Discharge (Kg/s)
Time (Day)
Observed SD
Estimated SD


H
Sediment Discharge (Kg/s)
Time (Day)
Observed SD
Estimated SD

V.4.2.2 Forecasting Suspended Sediment using Regularized Neural Network:

Table V-11 The performances of the regularized networks "Early Stopping criteria's" during training, validation and testing period.

ANN	INPUT COMBINATION	Epoch	Training		Validation		Testing	
			RMSE	R^2 (%)	RMSE	R^2 (%)	RMSE	R^2 (%)
ANN_9	WD_t	05	1.07	85.7	6.35	65.9	0.74	62.2
ANN_10	SSD_{t-1}	03	2.72	07.9	9.62	22.4	2.07	10.3
ANN_11	WD_t, WD_{t-1}	22	0.71	93.8	**6.11**	**68.8**	**0.84**	**66.0**
ANN_12	WD_t, SSD_{t-1}	12	1.06	86.0	6.58	63.9	0.83	60.3
ANN_13	SSD_{t-1}, SSD_{t-2}	73	1.72	63.2	9.77	20.2	3.26	04.0
ANN_14	WD_t, SSD_{t-1}, SSD_{t-2}	91	**0.36**	**98.4**	8.73	37.0	0.43	61.0
ANN_15	WD_t, WD_{t-1}, SSD_{t-1}	04	1.67	65.3	9.06	31.1	0.69	57.4
ANN_16	WD_t,WD_{t-1}, SSD_{t-1}, SSD_{t-2}	26	1.59	68.5	7.91	48.3	0.83	64.2

The performance results during training, validation and testing periods of the regularized neural networks depended on the input data from the Sebaou Wadi during training periods and the input data from the Isser Wadi used during validation and testing set.

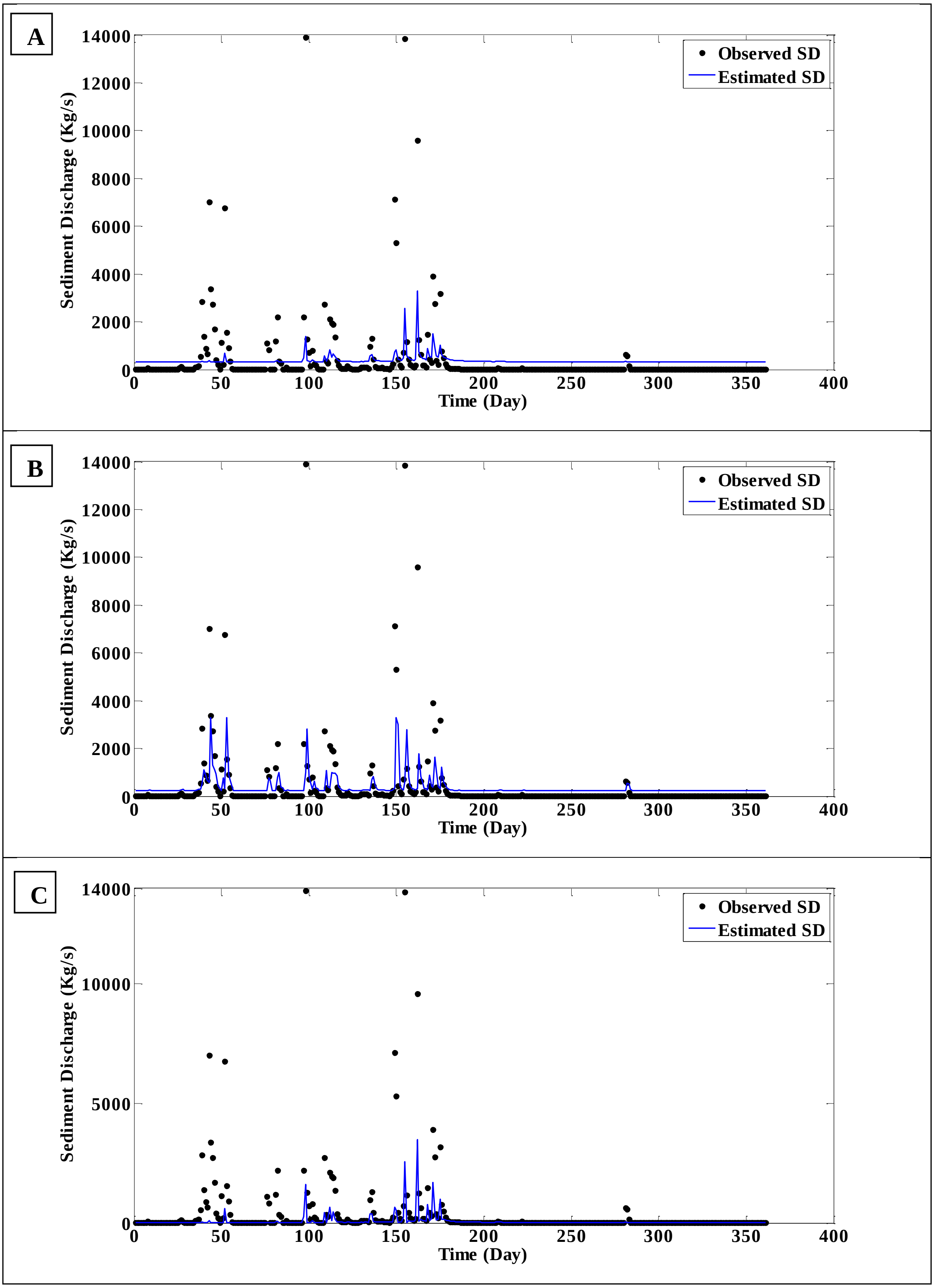
During the training set (table V-11) the R^2 and RMSE showed good values in the ANNs 9, 11, 12 and 14 with R^2 (85.7%, 93.8%, 86.0% and 98.4%).

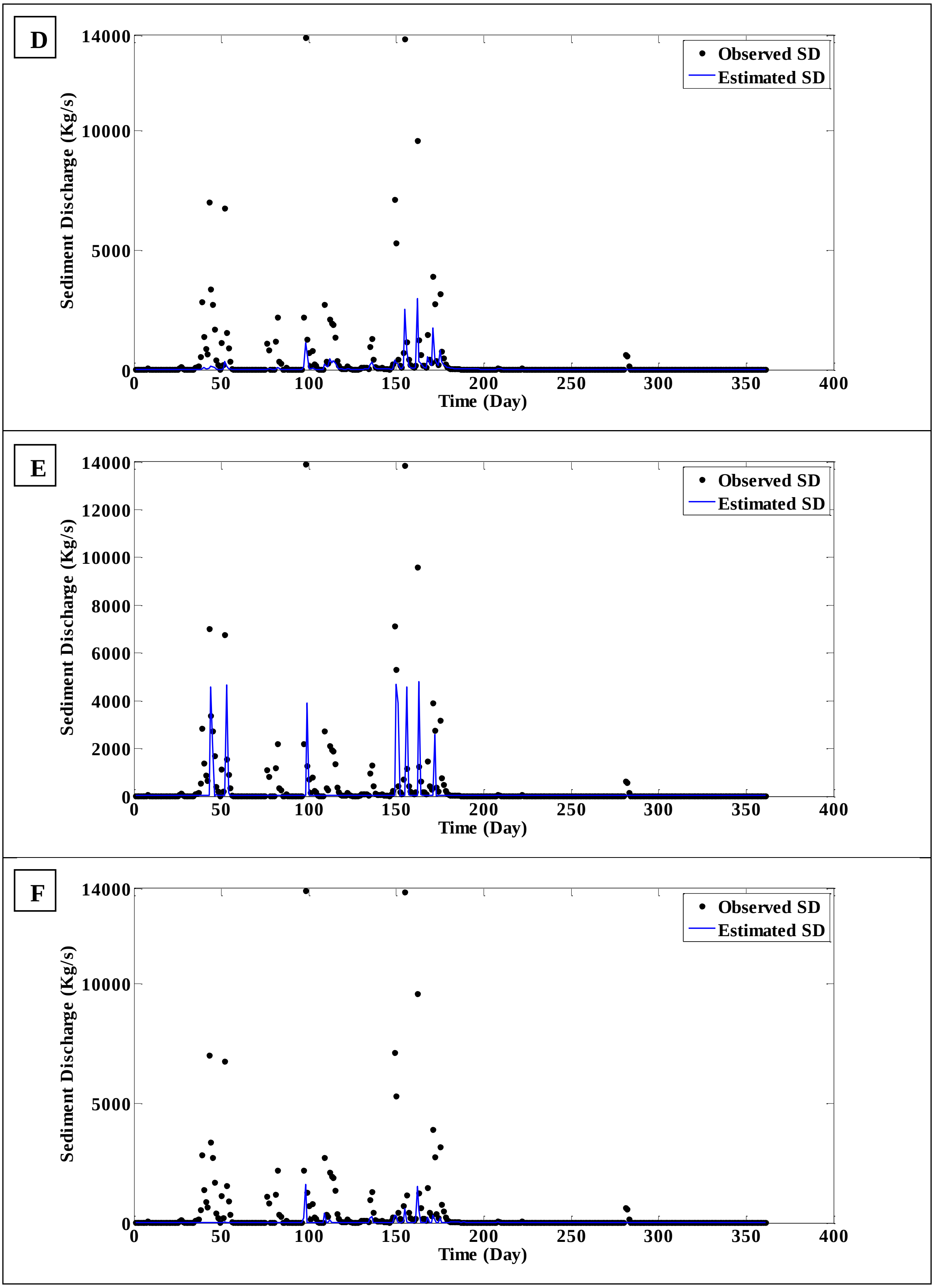
During the validation period the performances values showed poor coefficient of determination except ANN 9, 11 and 12 which showed average values with R^2 65.9%, 68.8% and 63.9% respectively.

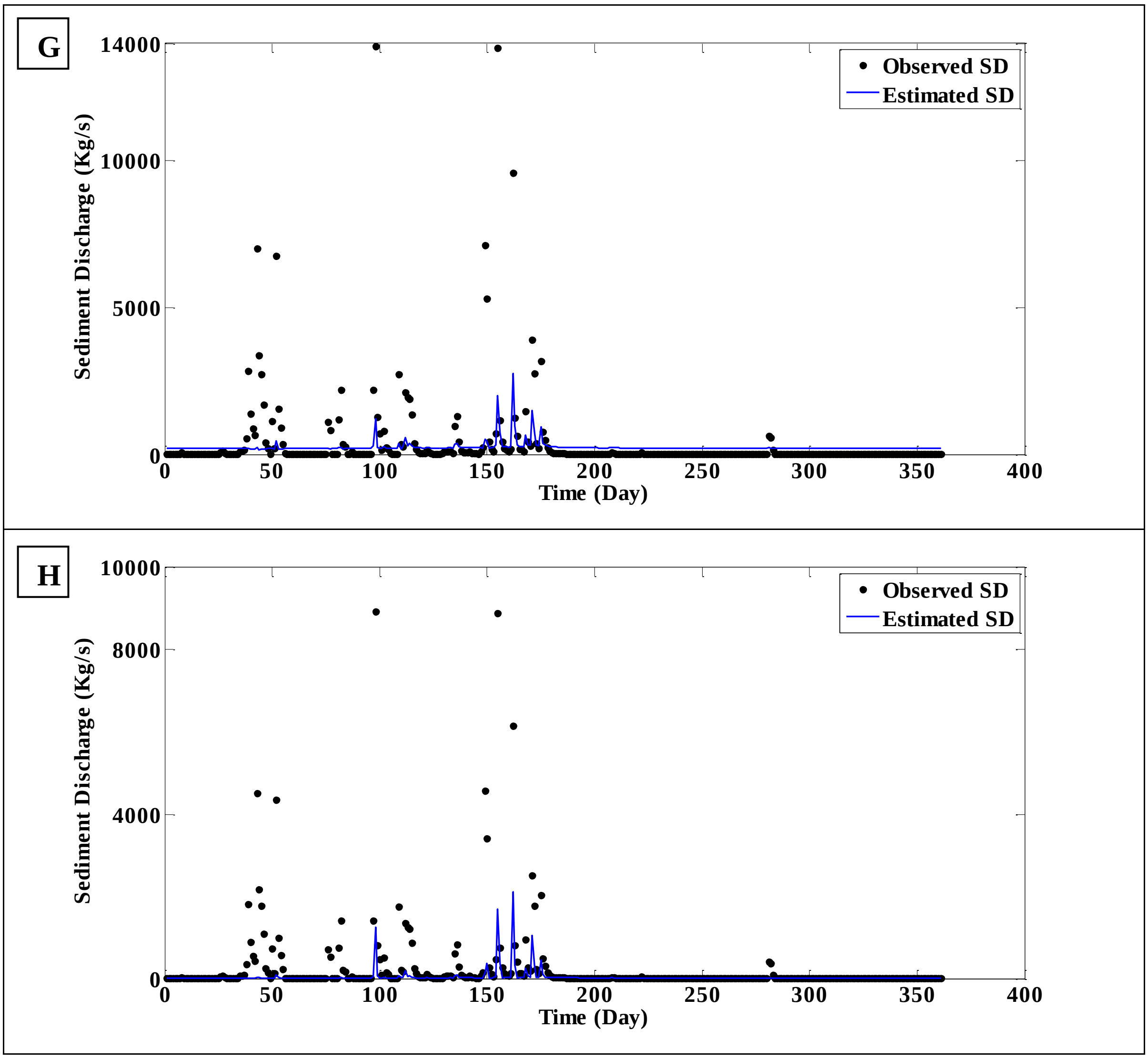
The RMSE and R^2 during testing period improved using the regularized neural networks comparing to the non regularized neural networks. The ANN 9, 11, 12, 14 and 16 showed as well average values with R^2 (62.2%, 66.0%, 60.3%, 61.0% and 64.2%) respectively. Even though the R^2 values showed average values between 60 to 65%, and still the networks didn't give good estimation of suspended sediment discharge. We can see clearly from figures that the under-estimation happened in most networks.

In this case of the estimation of the suspended sediment in ungauged Isser did not satisfy the prediction of this last phenomenon.

Figure V.10 The estimated and observed SSD using regularized NN in ungauged Isser.




D
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
5000
10000
14000
0
50
100
150
200
250
300
350
400
Time (Day)
E
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
2000
4000
6000
8000
10000
12000
14000
0
50
100
150
200
250
300
350
400
Time (Day)
F
Observed SD
Estimated SD
Sediment Discharge (Kg/s)
0
5000
10000
14000
0
50
100
150
200
250
300
350
400
Time (Day)



In general, it can be claimed that the use of neural network in the estimating of suspended sediment discharge in ungauged basin is very hard. Even though the used data of the ungauged basin was from nearby region had the same climatic factors and closely geological characteristics. But still the predictions of suspended sediment discharge in an ungauged catchment showed average values once using only current water discharge with standard back propagation neural network, and secondly using water discharge and previous values of sediment discharge. It is noticed that during the use of data of this ungauged catchment during testing period that the performance results R^2 and RMSE gave contradiction values. The performances values of the R^2 and RMSE must be checked together in order of knowing that the network didn't under-estimate or over-estimate the values. In many times the networks gave lower R^2 values but good RMSE and vice versa.

V.5 CONCLUSION:

The use of artificial neural network for suspended sediment prediction is very efficient. The application of the developed model in two different studied areas confirmed the ability of the neural network to model this phenomenon. The regularized neural network of both application on different studied areas confirmed that the over training in artificial neural network occurs especially when the inputs combinations and the introduced data are non linear and complex. The improvement of the predictive model increased till 80% in this study using the Early Stopping technique. The quality of this model was showed during the prediction of the ungauged watershed of closed area. The neural networks showed acceptable results of some models in forecasting the suspended sediment discharge of both watersheds depending on input data of each others. The results of the ungauged watershed using neural networks could support the researchers for the estimation of sediments in non controlled Wadis in the Maghreb region.

VI. CONCLUSION

The processes of flow and sediment load are complex in Algeria. The study investigated the comparison between non regularized and regularized ANN using the Early Stopping technique for predicting suspended sediment discharge on a daily scale in three cases. The first case was applied on the Isser Wadi, upstream of the Beni Amrane reservoir. The second case was applied on the Sebaou Wadi, in the Great Kabyle watershed. In the third case, the input data of the Sebaou Wadi was used to estimate the sediments in the Isser Wadi and vice versa.

In the first step, we compared regularized and non regularized neural network using the Early Stopping technique for forecasting the suspended sediment discharge in the Isser Wadi on daily scale. In this application we used different input combinations including daily current and previous water discharge and previous sediment discharge in the ANN models to obtain the optimal input combination. The results obtained in this application indicated that over-fitting occurred in the networks, and the use of the Early Stopping technique performs better results with the predictive models comparing to non regularizing networks. The major over-fitting that occurred in the ANN model was when we used previous values of sediment discharge.

In the second step, we went thru the same steps of the first application on different study area. In this application we forecasted the sediment discharge of the Sebaou Wadi, Great Kabyle watershed. The same input combinations were introduced to the neural network in order of comparison of the obtained ANN models on different studied areas. The results indicated that the over-fitting occurred as well in the networks, and the Early Stopping technique improved the performances results comparing to non regularized networks. In order of comparison of the results between the used studied areas, it can be noticed that the first application on the Isser Wadi gave better results comparing with the application of the Sebaou Wadi, and we expect this superiority to the large database that we used in the first application (Thirty years) comparing to the second application on the Sebaou Wadi (8 years).

In the third application, we compared regularized and non regularized neural network in forecasting the suspended sediment loads in an ungauged watershed.

Firstly, we used the input data of the Isser Wadi (Lakhdaria hydrometric station) during training period for estimating the sediment discharge of the Sebaou Wadi. And secondly, we introduced the input data of the Sebaou Wadi during training period to estimate the sediment discharge of the Isser Wadi.

The results indicated that the use of regularized ANN in ungauged nearby basin from the same climatically and geologically characteristics gave acceptable values only in one Wadi, where we used the input data of Isser during training period. The acceptable results of this last were due to the homogeneity of the data of the Isser Wadi. The non regularized neural network showed very high over-fitting and the regularized neural network showed high under-fitting because of the complexity and the big size of data that were introduced to the networks. For better estimation of sediment discharge in ungauged basin the models input should depend on more climatic and hydrologic parameters of couple nearby watersheds.

In conclusion, we have shown that forecasting suspended sediment discharge using the Early Stopping criterion's in ANN modelling is very robust and effective. We have also shown that forecasting suspended sediment discharge in ungauged basin from the same climatic and geological characteristics gave average results using neural networks and could support the modelling of sediment load in ungauged watershed.

In the future we aim to use different regularized neural networks techniques in gauged and ungauged watersheds to avoid erosion, sedimentation and dam silting in different Wadis in Algeria. Among these techniques; noise injection and optimized approximation algorithm in artificial neural network to avoid over-fitting and to improve the networks for better results.

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