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WEPP and ANN models for simulating soil loss and runoff in a semi-arid Mediterranean region

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Abstract This paper presents the use of both the Water Erosion Prediction Project (WEPP) and the artificial neural network (ANN) for the prediction of runoff and soil loss in the central highland mountainous of the Palestinian territories. Analyses show that the soil erosion is highly dependent on both the rainfall depth and the rainfall event duration rather than on the rainfall intensity as mostly mentioned in the literature. The results obtained from the WEPP model for the soil loss and runoff disagree with the field data. The WEPP underestimates both the runoff and soil loss. Analyses conducted with the ANN agree well with the observation. In addition, the global network models developed using the data of all the land use type show a relatively unbiased estimation for both runoff and soil loss. The study showed that the ANN model could be used as a management tool for predicting runoff and soil loss.

Keywords Land use · Soil properties · Runoff · Water erosion · Erodibility · Erosivity · WEPP · Artificial neural network · Palestine

Introduction

Reduction of soil erosion to preserve soil quality and to maintain land productivity constitutes a major challenge for mountainous soils. Soil erosion can be reduced by appropriate land management. It requires both the collection of field data and the development of predictive model for the evaluation of different management scenarios for the protection of soils. Field measurements of erosion and sedimentation using classical techniques is time-consuming and expensive (Bujan et al. 2000). The modelling of the erosion process has progressed rapidly, and a variety of models have been developed to predict both the runoff and soil loss (Zhang et al. 1996).

Several software have been developed to predict the soil erosion and the corresponding nutrient losses from agricultural runoff, for example, GWLF (Schneiderman et al. 2002), SMDR (Gérard-Marchant et al. 2005) and SWAT (DiLuzio and Arnold 2004). However, a full

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understanding of the nutrient transport process is difficult. In addition, large data input requirements may restrict the use of comprehensive simulation models (Bhattacharya and Solomatine 2000). Therefore, researchers have sought alternative predictive procedures.

The Water Erosion Prediction Project (WEPP) (Nearing et al. 1989) is a frequently used to simulate the water erosion and sediments (Merrit et al. 2003). It has been tested and applied in various geographic locations across the USA (Laflen and Roose 1997), Australia (Yu and Rosewell 2001) and Europe (Brazier et al. 2000; Grønsten and Lundekvam 2006). Analyses showed that the WEPP performed well in USA (Brazier et al. 2000). The use of the WEPP in steep alpine environments has been reported in the Italian Alps (Simonato et al. 2002). Analyses well agreed with the field data. However, hydrological parameters were not measured. Hence, the overall quality of the total model output could not be verified.

During the last decade, Artificial Neural Networks (ANNs) have been used as an alternative modeling method. ANNs were successfully used in fields close to the soil erosion phenomena. The American Society of Civil Engineers Task Committee on Application of Artificial Neural Networks in Hydrology (2000) reported application of the ANN for rainfall–runoff modeling, stream flow forecasting, groundwater modeling, water quality, water management policy, precipitation forecasting, hydrological time series and reservoir operations. The artificial neural network was mainly used for classification of the erosion processes. De la Rosa et al. (2000) captured interactions between the land and land management qualities and a vulnerability index to soil erosion in Andalucia region in Spain by means of expert decision trees and artificial neural networks. Harris and Boardman (1998) used the expert systems and neural networks as an alternative paradigm to mathematical process-based erosion modeling for South Downs in Sussex, England. Licznar and Nearing (2003) used the neural networks to quantitatively predict the soil loss from natural runoff plots, utilising 2,879 erosion events from eight locations in the USA. They indicated that the neural networks performed generally better than the WEPP model in predicting both event runoff volumes and soil loss amounts. Pachepsky et al. (1996) reported that the ANN's estimated soil water content better than regression techniques. Starrett et al. (1996) reported that an ANN performed better ($r^2 = 0.984$) than a regression model ($r^2 = 0.780$) in predicting applied-nitrogen leaking below the root zone of turf grass.

Material and methods

Study area

The Palestinian Territories (PT) is located to the east of the Mediterranean Sea between 29° and 33° North latitude and between 35° and 39° longitude (PEnA 1999). Located at the meeting point between Eurasia and Africa, specifically in the southeastern corner of the Mediterranean sea, it creates unique topography and ecosystems (Fig. 1). It is worth mentioning that PT refers to the West Bank and Gaza Strip. The PT has a total area of about 6,210 km^2(5,845 km^2 in the West Bank and 365 km^2 in Gaza Strip) (Ministry of Agriculture 2004a, b). The West Bank is characterised by a great variation in topography and altitude, where variations range between 1,020 m above sea level and 375 m below sea level (PEnA 1999).

The West Bank is classified into four major ecosystem based on several factors including climate, topography and soil types. These systems are the Jordan Valley region, the Eastern Slopes region, the Semi Costal region and the Central Highlands region. The central highland region extends the length of the West Bank with the most populated and accessible area to the Palestinian people. This is the largest region in the West Bank with an approximate area of 3,500 km^2 (PEnA 1999). Its length is 120 km including the area from Jenin in the north to Hebron in the South. It is mountainous with some areas exceeding an elevation of 1,000 m above sea level. It has a good average of annual rainfall ranging between 400 mm in the Southern foothills and about 700 mm in the mountainous areas (Dudeen 2001).

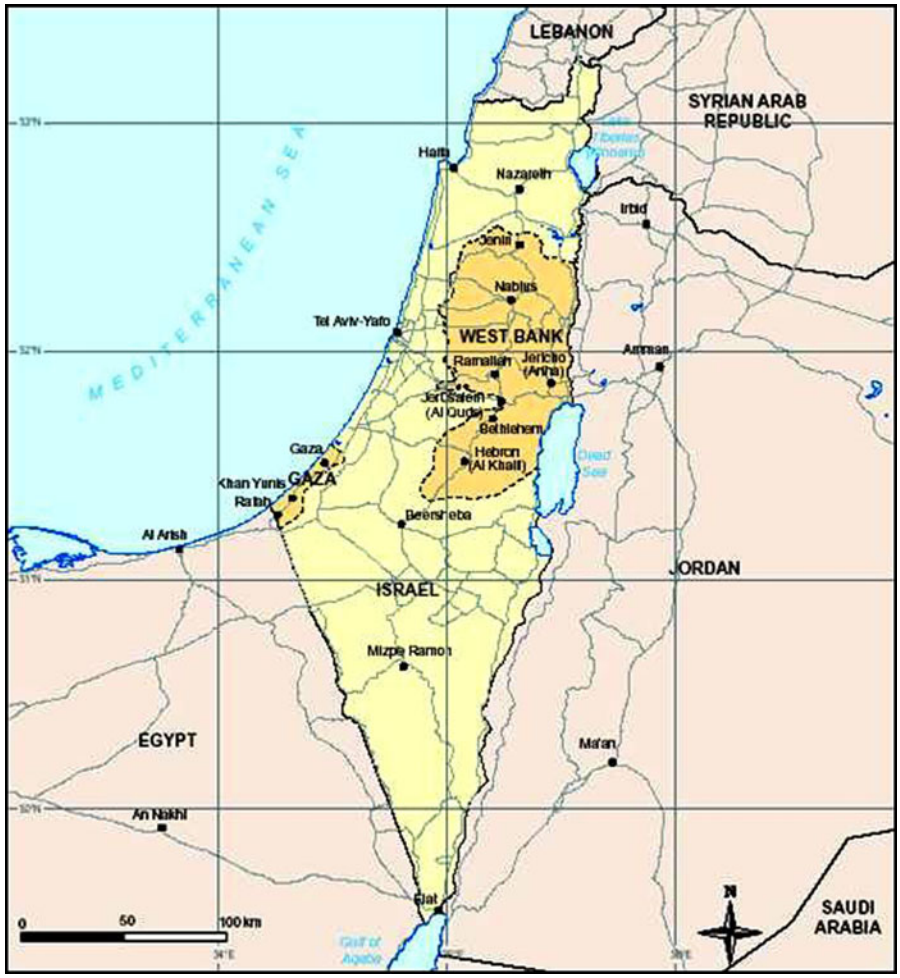


Fig. 1 Geographical projection of the study area

The vast majority of the cultivated area in the highlands is rainfed. Since old history, the olive cultivated hills gave the west bank landscape a particular character. Of the total agricultural area, olives and grapes predominate, and with almonds and fruit trees occupying 60% (PEnA 1999). This region was selected because:

Field inspection of the Palestinian territories shows that soil erosion is present almost everywhere and is particularly severe on bare, compact ground near residences and other buildings (Soil and Water Conservation Society 1994; Abu Hammad 2004).

Water erosion causes severe problems to the population that live in the central highlands, such as loss of soil from arable farmland, reduction in public investments in infrastructure works and degradation in urban areas (Ministry of Agriculture 2004a, b).

Based on the Palestinian Agricultural Strategy, the Palestinian Ministry of Agriculture (MOA) should assess the extent of both the soil erosion and desertification and identify priority actions and areas where mitigation measures are most needed. The MOA should also give high priority to set up an effective mechanism for the regular monitoring of the soil erosion and desertification (Ministry of Agriculture 2004a, b).

The present study relied on a very important project (Regional Initiative for Dry land Management, DIM) conducted by the Palestinian Ministry of Environment and International Centre for Agricultural Research in Dry Area, under the auspice of the World Bank.

Data collection

Understanding the different factors that affect soil erosion problem in the Palestinian Central highland mountainous area, it is a prerequisite for modelling and predicting the soil loss under this condition. The runoff and soil erosion factors were collected during 2 years in five major land uses in the central highland. The data concerned the runoff, soil loss, vegetation cover, rainfall and rainfall intensity, topography including the slope and slope length, and the soil physical and hydraulic properties.

The study showed that the rainfall intensity was very low, with only a few rainfall events with considerable intensity and kinetic energy, which may cause a real damage to the soil surface.

Data analysis showed low soil erodibility in comparison with the standard soil erodibility. The most erodible soils are located under the vineyard non-terraced land use, while the best resistance soils correspond to the forest land use. Unfortunately, there are no rill and inter-rill erodibility data for comparison with other soils in the region. The presence of annual vegetation and plant residues on the soil surface and the terracing structures induce an important reduction of soil loss. Analyses show of a strong positive relation between sediment loss and the rainfall depth and runoff.

The lowest rates of runoff and sediment loss are located in the forest under semi-natural conditions, i.e. with undestroyed vegetation of annual plants, under this land use, annual vegetation and plant residues have a high soil surface cover, occasionally up to 85% of the ground, to prevent surface sealing and minimising the velocity of the runoff water.

Methods

The field data come mainly from the Regional Initiative Project for Dry Land Management coordinated by the Palestinian Ministry of Environment in the period 2003/2004–2004/2005. To understand the issue of soil erosion, five land use types were investigated at small scale, which represented the major land use present in the study area. The data were then used for the verification of some modelling techniques and procedures proposed for predicting the soil erosion and runoff. The performances of these methods were compared in order to select the appropriate predictive model.

Presentation of the WEPP

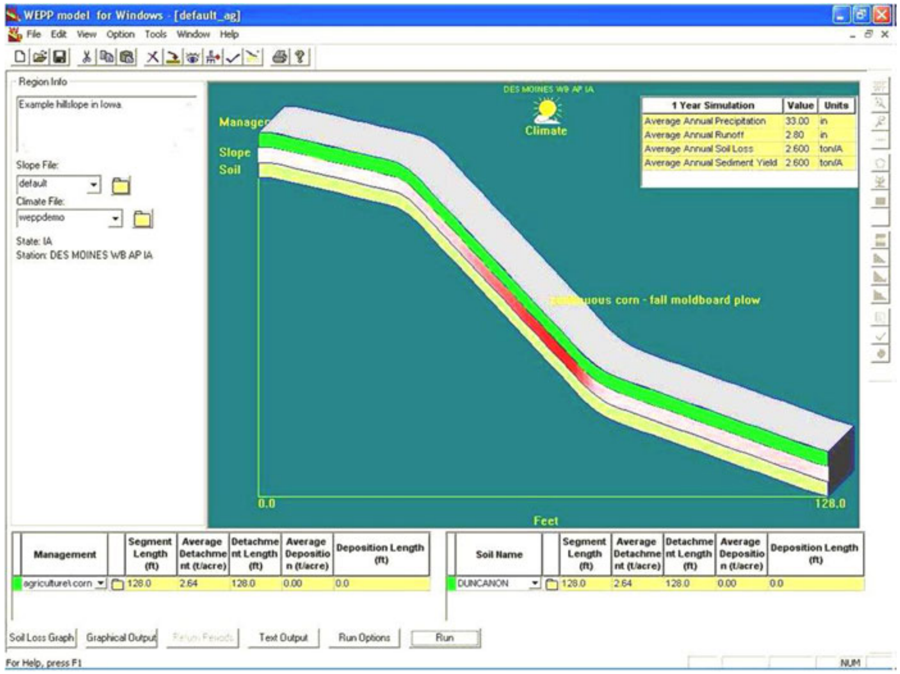
The WEPP software includes an erosion prediction model, a climate generator program and a Windows interface (Flanagan and Frankenberger 2002). The main Windows interface screen shows a graphical illustration of a hillslope profile, with various areas providing access to input databases and output display (Fig. 2). The profile shape is drawn based upon the model slope inputs, which can be accessed through the middle layer on the graphic. Soil information can be accessed through the bottom layer on the graphic and the cropping/management information through the top profile layer. Climate inputs can be selected or generated through the icon at the top centre of the screen. The data include four files: climate, slope, soil and plant management.

Input data for the model

The WEPP is used for simulating the soil loss form single storm rainfall events for the five land use types in the Palestinian Central Highland mountainous area: forest (LU1), natural vegetation (LU2), Olive groove (LU3), vineyard terraced (LU4) and vineyard non-terraced (LU5).

Data collected from the study area used to construct the climate files for single event simulations of WEPP. Amount and duration of rainfall, maximum and minimum temperature, solar radiation, wind velocity and dew temperature are required on a daily basis. Two years of data were used in the study. Soil input file and slope file were prepared using graphical user interface included in the model. Model parameters such as organic matter content, percentage clay, percentage silt, percentage sand and percentage rock fragment were obtained from the soil analysis data and also from the soil database prepared by the Land

Fig. 2 WEPP windows interface



Research Centre. The baseline effective hydraulic conductivity, inter-rill erodibility parameter, rill erodibility parameter and critical flow hydraulic shear stress values for WEPP were estimated as described in the WEPP user manual (Albaradeyia 2007). Management input files were built for the different land use types from the management data and information obtained from the study area. Due to the lack of some information about the land use data required to prepare the management file, a suitable management data was elaborated from the WEPP database and user manuals.

Evaluation criteria

Runoff and soil loss were simulated for all rainfall events in 2003–2005 for the different land use types. The models were evaluated by fitting regression equations between the predicted values and the observed values. The performances of fit of the equations to the data were evaluated using the coefficient of determination and the standard error of estimate. The greater the values of R^2, the better will be the fit of the data to the equations and the closer the simulated values to observed values. Also, the slope of the regression equations (b) closes to unity means unbiased the prediction. A slope value <1 indicates an under prediction, while a slope >1 indicates an over prediction. The analysis of variance was performed by comparing the standard deviations of the observed and predicted values. A particular interest was considered for the confidence interval for the ratio of the variances. If the ratio of variances does not contain the value 1, there is a statistically significant difference between the standard deviations of the two samples at the 95% confidence level.

ANN description

The ANN learns from the input data and the associated output data, which is commonly known as the generalisation ability of the ANN (Hassan 2001). Multilayer Perceptrons is the most popular network architecture. To develop and train a NN involve, choosing a training set that contains input–output pairs; defining a suitable network (number of layers and number of neurons in each layer); training the network to relate the inputs to the corresponding outputs by estimating the NN weights; and testing the identified NN. Typically the data available for NN calibration is split in three parts: training, testing and validation.

As shown in Fig. 3, three-layered feed forward neural networks with one hidden layer, which have been used in this research, provide a general framework for representing nonlinear functional mapping between a set of input and output variables. The explicit expression for an output value of the network model is given by:

$$\hat{y}_k = f_0\left(\sum_{j=1}^{M} w_{kj} \cdot f_h\left(\sum_{i=1}^{N} w_{ji}x_i + w_{j0}\right) + w_{k0}\right)$$

Where w_{ji} is a weight in the hidden layer connecting the ith neuron in the input layer and the jth neuron in the hidden layer, w_{jo} is the bias for the jth hidden neuron, f_h is the activation function of the hidden neuron, w_{kj} is a weight in the output layer connecting the jth neuron in the hidden layer and the kth neuron in the output layer, w_{ko} is the bias for the kth output neuron, and f_o is the activation function for the output neuron. The weights are different in the hidden and output layer, and their values can be changed during the process of network training.

The relationship between the input variables and the output variables is generated by the training process. In this study, training is accomplished by a backpropagation algorithm, as shown in Fig. 3. The weights are adjusted so as to make the actual response ($\hat{y}_k$) of the network closer to the desired response (y_k). The objective of the backpropagation training process is to adjust the weights of the network to minimise the sum of square errors of the network:

$$E(n) = \frac{1}{2}\sum_{k=1}^{k}\left[y_k(n) - \hat{y}_k(n)\right]^2$$

$\hat{y}_k(n)$ is the desired target responses and y_k is the actual response of the network for the kth neuron at the nth iteration. The process of feed forward and error back propagation is repeated until the determination of the minimum of $E(n)$ (Liu et al. 2003).

Each hidden node (j) receives signals from every input node (i) which carries scaled values ($\bar{X}_i$) of an input variable where various input variables have different measurement units and span different ranges. $\bar{X}_i$ is expressed as:

$$\bar{X}_i = \frac{X_i - X_{\min(i)}}{X_{\max(i)} - X_{\min(i)}}$$

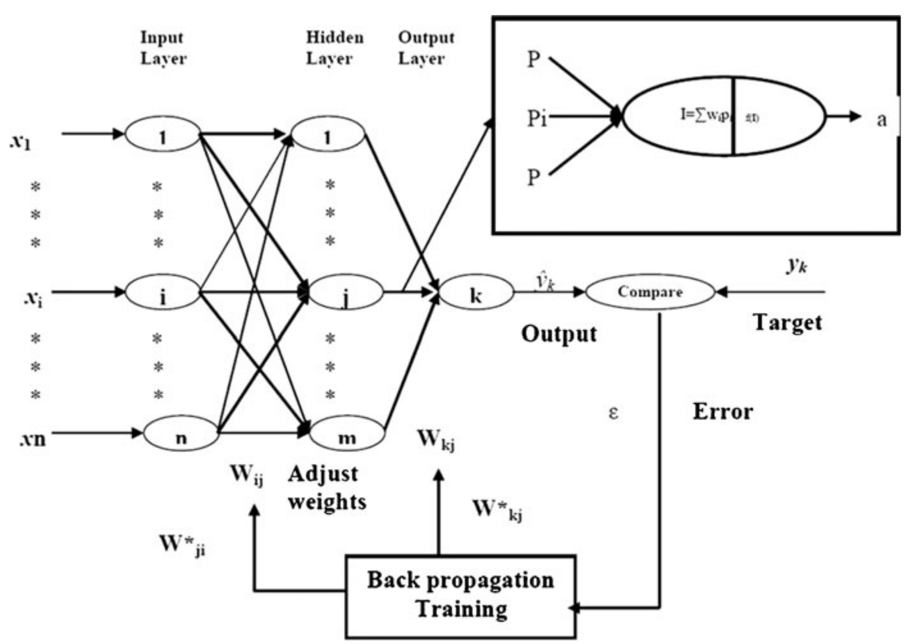


Fig. 3 Typical three layered feed forward neural networks with a back propagation training algorithm

Each signal comes via a connection that has a weight (W_{ij}). The net integral incoming signals to a receiving hidden node (Net_j) is the weighted sum of the entering signals, $\bar{X}_i$, and the corresponding weights, W_{ij} plus a constant reflecting the node threshold value (TH_j):

$$\mathrm{Net}_j = \sum_{i=1}^{n} \bar{X}_i W_{ij} + \mathrm{TH}_j$$

The net incoming signals of a hidden node (Net_j) is transformed to an output (O_j) from the hidden node by using a non-linear transfer function (f) of sigmoid type (Najjar and Zhang 2000), given by the following equation form (Fig. 4):

$$O_j = f\left(\mathrm{Net}_j\right) = \frac{1}{1 + e^{-\mathrm{Net_j}}}$$

This function then turns this number into a real output via some algorithm. This algorithm takes the input and turns it into a zero or one, a minus one or one, or some other number. Q_j passes as a signal to the output node (k). The net entering signals of an output node (Net_k)

$$\mathrm{Net}_k = \sum_{i=1}^{n} O_j W_{jk} + \mathrm{TH}_k$$

The net incoming signals of an output node (Net_k) are transformed using the sigmoid type function to a standardised or scaled output ($\bar{O}_k$) that is:

$$\bar{O}_k = f\left(\mathrm{Net}_k\right) = \frac{1}{1 + e^{-\mathrm{Net_k}}}$$

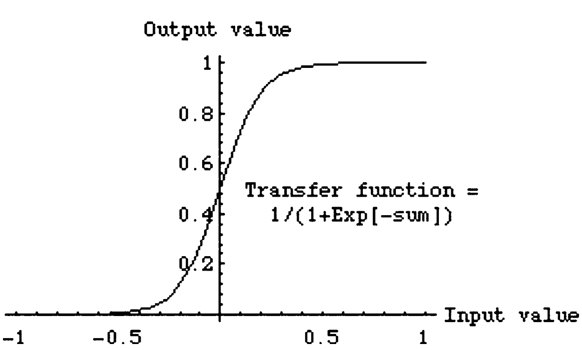


Fig. 4 Sigmoid transfer functions

Then, $\bar{O}_k$ is de-scaled to produce the target output:

$$O_k = \bar{O}_k\left(O_{\max(k)} - O_{\min(k)}\right) + O_{\min(k)}$$

The neurons in a layer share the same input and output connections, but do not interconnect among themselves. Each layer performs specific functions. All the nodes within a layer act synchronously, meaning at any point of time they will be at the same stage of processing.

ANN program

The TR-SEQ1 artificial neural network program (Najjar 1999) was used. It is capable of performing simultaneous sequential training and testing. It is a comprehensive, powerful and less time consuming package and characterised by intelligent problem solver that can guide step by step through the procedure of creating a verity of different networks and choosing the network with the best performance (Eila 2005). The program use Multilayer Preceptrons (MLPs) network architecture with back propagation feed forward algorithm for training the network.

Running the program includes three phases: training, testing and validation. In our work, it is divided into parts as follow, 50% for training, 25% for testing and 25% for validation.

Evaluation criteria

Building the ANN model requires a clear definition the performance criteria (Maier and Dandy 2000). The coefficient of determination (R^2), the average squared error (ASE) and the mean absolute relative error (MARE) were used for the performances determination. The optimal ANN model's structure that resulted in minimum error and maximum efficiency during both training and testing was selected for validation. The values of both ASE and MARE close to zero indicate a good performing model. The values of R^2 range from 0 to 1, with higher values close to 1 indicating good performance.

A particular interest was considered to the confidence interval for the ratio of the variances. If the ratio of variances does not contain the value

1, there is a statistically significant difference between the standard deviations of the two samples at the 95% confidence level.

Network development

Two types of networks were elaborated. The first one is a Global network for the five land use types, while the second is Individuals; it concerns each land use type individually. For the Global network, three networks were developed:

NET1 for both runoff and erosion
NET2 for the runoff only
NET3 for the erosion only

Input file for NET1 consisted in 365 rainfall events values and 10 input parameters including: rainfall event depth, event duration, maximum 30-min intensity, incident soil moisture, slope, slope length, support practices, maximum 30-min intensity kinetic energy, vegetation cover and maximum daily temperature. Input file for NET2 was developed with the first nine parameters which have been already considered for NET1 and excluding the maximum daily temperature. The input parameters for NET3 were the same 10 parameters used in NET1, except that the maximum daily temperature, which was replaced by the average daily wind speed.

Input file for each individual land use type designed for simulation both the runoff and soil loss, included a small number of data set (73 rainfall events). Nine input parameters were used for both NETLU1 and NETLU3. Modelling neglected the slope steepness, slope length and vegetation cover, which were constant for these two land use. Seven input parameters were used for NETLU2, NETLU4 and NETLU5. Modelling included the vegetation cover, since varied with the period of the rainy season under these land use. All the rainfall events were considered either they are yielding runoff and soil loss or not in the network training.

The main soil erosion factors which have been reported in the literature were considered for developing the soil loss and runoff networks. Input parameters were carefully analysed together with additional parameters considered important by the WEEP model (Table 1). The maximum daily temperature has shown a positive contribution to the performance of NET1. The average daily wind speed also contributed positively to the performance of NET3 (Table 2).

Table 1 Effect of some of the parameters considered by WEPP in ANN networks

COMINATION	NET1	NET2	NET3
NETs with the 9 parameters	81	87	88
Clay%	78	87	88
Bulk density	81	86	87
Total porosity	78	87	88
OM%	78	85	88
H. conductivity	78	84	88
Max. temperature	87	83	87
Min. temperature	82	85	84
Avg. wind speed	82	85	90
Kr	78	84	88
Ki	80	87	87

Sensitivity analysis was carried out to determine the effect of some additional parameters. The Kinetic energy of the maximum 30-min intensity (Table 3) was the most influential parameter that contributes to the performance of all the networks, followed by incident soil moisture, Maximum 30-min intensity, maximum daily temperature and rainfall event duration.

As mentioned by Albaradeyia (2007), the number of neurons in the hidden layers cannot be determined from a universal formula; in this research, we used the formula recommended by Najjar (1999) to estimate the initial number of neurons, to prevent over-fitting. Najjar suggested that the initial appropriate number of neurons in a hidden layer can be calculated by $(T - O)/(I + O + 1)$, where T is the number of training set, O is the number of output variables and I is the number of input variables.

Table 2 Significance of the selected parameters on the NET1 performance

Input	R^2 testing	ASE testing
NET1	87	0.004482
NET1—Max I30KE	72	0.000024
NET1—Incident moisture	75	0.008659
NET1—Max.I30	76	0.006653
NET1—Temperature	81	0.006300
NET1—Event duration	81	0.007289

Table 3 NET1 testing phase with different architecture and neuron in the hidden layer

Model	Architecture	Iteration	No. initial neurons	No. optimal neurons	ASE testing	R^2 testing
1	10–1–2	500	1	8	0.004482	0.87
2	10–2–2	1,000	2	6	0.00562	0.85
3	10–3–2	1,900	3	4	0.007988	0.77
4	10–4–2	9,900	4	6	0.004889	0.86
5	10–5–2	10,000	5	7	0.006731	0.79
6	10–6–2	9,900	6	10	0.005605	0.83
7	10–7–2	1,000	7	7	0.005899	0.83
8	10–8–2	400	8	8	0.00875	0.77
9	10–9–2	400	9	9	0.007481	0.76
10	10–10–2	100	10	10	0.007710 0	0.78

Results and discussion

Analysis of the soil erosion

The soil erosion is a complex phenomenon resulting from numerous interacting factors: soil, topography, land cover and climate (Wischmeier and Smith 1978). Runoff is the main factor of the soil erosion by water (Hudson 1995). The soil erosion by water is considered as the main land degradation and desertification process leading to progressive inability of vegetation and soils regeneration (Mainguet 1994).

Runoff response and the soil erosion are highly variables under different land use and management practises. Different management practices under the different land use types have a significant effect in soil physical and hydraulic properties. The erosion, to lesser degree, is also influenced by the soil surface characteristics (Agassi 1995). The findings of the interpretation of vegetative cover, soil physical and hydraulic properties and erosion and runoff data under the different land use types obtained from the study, based on rainfall events were elaborated by Albaradeyia (2007).

The presence of annual vegetation and plant residues on the soil surface and the terracing structures are responsible for the reduction of the soil loss to very low values; therefore, further degradation of the land is restricted. The results confirm the existence of a strong positive relation between both the rainfall depth and the runoff and the sediment loss for particular different kinds of land use and between runoff and the soil loss with the presence or absence of the support practices as terraces in the region.

The lowest rate of runoff and sediment loss were found in Forest grown under semi-natural conditions, i.e. with undestroyed vegetation of annual plants, under this land use, annual vegetation and plant residues have a high soil surface cover, occasionally up to 85% of the ground, to prevent surface sealing and minimising the velocity of the runoff water. The greatest rates of runoff and soil erosion were observed under vine yard none terraced, which possess favourable conditions for water runoff and sediment loss.

The decrease in the vegetation cover and the increase in mechanical activity under the cultivated land use resulted in a significant decrease in the soil organic matter, aggregate stability and the hydraulic conductivity and the total porosity and the effective porosity of the soil.

Despite the dispersion of the collected data, due to different soil surface properties, slope grade and length, we observe a tendency of increasing runoff and sediment loss with decrease in the vegetation cover and insufficient preventive, where the soil surface remains bare and thus very susceptible to raindrop impact, runoff and soil erosion. The application of a suitable management practices (terraces, vegetation cover and others) is essential to minimise the erosivity of the rainfall and reduce both runoff and erosion.

In conclusion, when the cultivated land utilised without proper practices of securing organic matter and soil stability, they are easily threatened and exposed to runoff and soil erosion. Therefore, the measure should be implemented to sustain the land and prevent them from degradation.

Validation of the hillslope WEPP model

Runoff

The plot of the observed and predicted soil loss values computed using the WEPP model for all land use types are shown in Fig. 5a–e. The WEPP Hillslope model simulated lower runoff events than measured for all land use types during 2003–2005. In particular, the runoff values were underestimated by the WEPP model as shown by the slope values of the regression equations (Table 4) and the small runoff events (<2 mm) were mostly missed. This type of response was also observed by Soto and Diaz-Fierros (1998) were runoff events (<mm) were simulated with no runoff, and by Grønsten and Lundekvam (2006) were small runoff events (<5 mm) were mostly missed. The WEPP model simulated less surface runoff than measured for all land use types (Table 5). Best agreement between measured and simulated runoff were obtained with LU5, with 50% of measured surface runoff ($R^2 = 0.67$). Simulated surface runoff for the other land use types, LU1, LU2, LU3 and LU4 was 10%, 34%, 38% and 30%, respectively, of measured values. Testing the statistical difference between the observed and

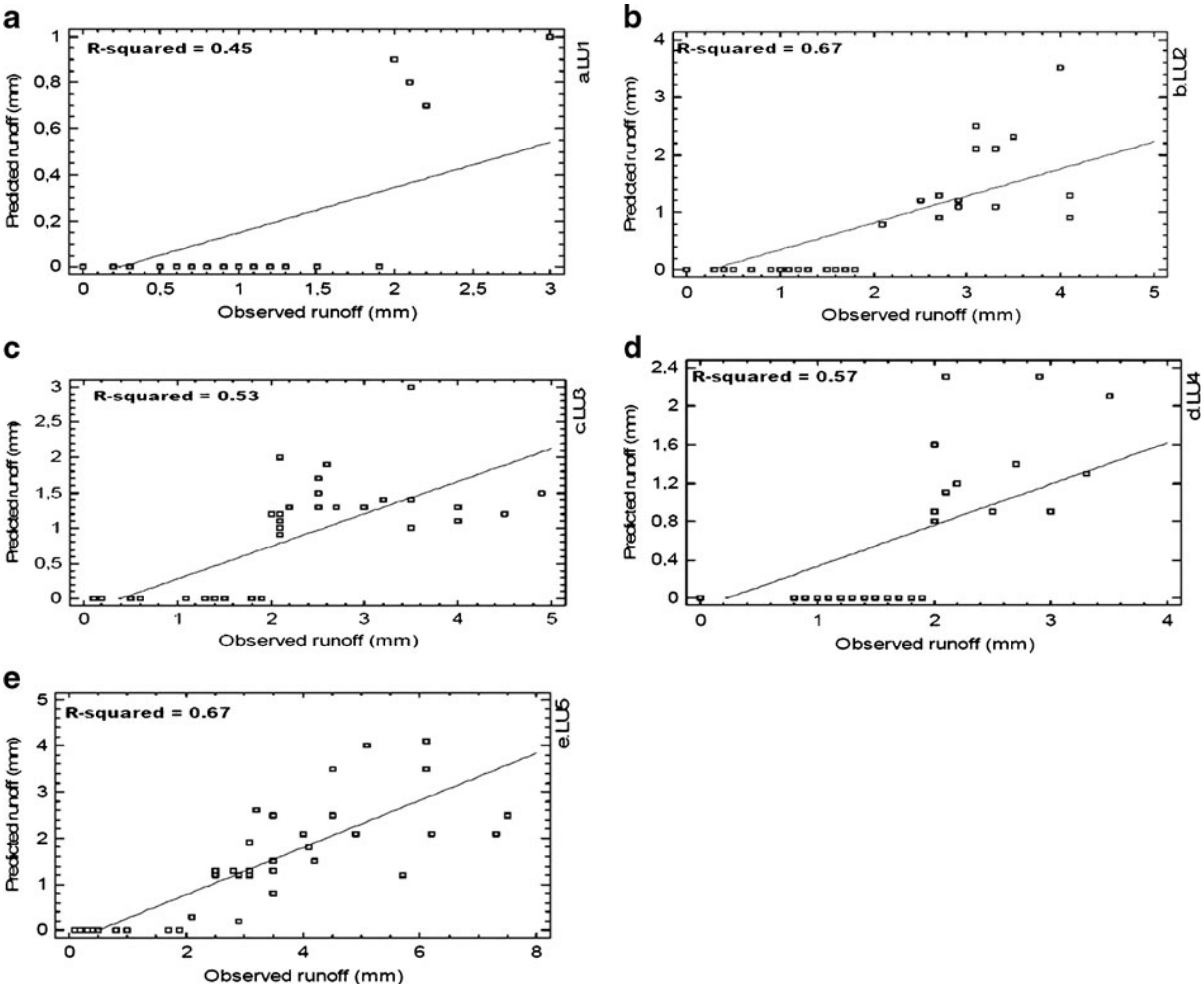


Fig. 5 **a–e** Observed vs. WEPP predicted runoff under the five land use types

Table 4 Summary statistics of the WEPP model validation for runoff according to the land use types

Statistics	LU1	LU2	LU3	LU4	LU5
R^2	0.45	0.67	0.53	0.57	0.67
σ	0.146666	0.409234	0.54	0.374029	0.737677
b	0.195736	0.468384	0.459995	0.42877	0.511398
Ratio of variances	[7.38851; 18.7505]	[1.93524; 4.91121]	[1.32119; 4.80471]	[1.94334; 4.93177]	[1.41328; 4.7468]

predicted values shows that there is a significance difference between observed and predicted values for all land use types as indicated by the ratio of variances (Table 4). Since the ratio of variances does not contain the value of 1, it indicates that the predicted values are not within the range of observed values.

Soil loss

The WEPP hillslope model under estimated the runoff, and consequently, the soil loss for the five land use types. Soil loss was underestimated as shown by the slope values of the regression equations (Table 6), and in some cases, the model completely failed to predict the soil loss, predicting values equal to 0 (Fig. 6a–e). This type of model response was also observed by Bowen et al. (1998), Bhuyan et al. (2002), Chitrakar (2004) and Romero León (2005). The WEPP model simulated lower soil loss than measured for all land use types (Table 5).

Best agreement between measured and simulated soil loss was obtained with LU5, with 46% of measured total soil loss ($R^2 = 0.75$). Simulated soil loss for the other land use types, LU1, LU2, LU3 and LU4 was 20%, 34%, 37% and 25%, respectively, of measured values. Testing the statistical difference between the observed and predicted values shows that there is a significant difference between observed and predicted values from all land use types as indicated by the ratio of variances (Table 6). Since the ratio of variances does not contain the value of 1, it indicates that the predicted values are not within the range of observed values.

Due to the variability and uncertainty of erosion data under field conditions, an error in the model prediction up to 50% has been considered acceptable by some researchers (Kothyari et al. 1993). At best, any predicted runoff or erosion value, by any model, will be within only ±50% of the true value (Elliot et al. 2000). The failure in predicting the soil loss and runoff under the studied condition could be the reason that of the model are mostly dependent on the high rainfall intensity. According to Risse et al. (1994), some studies have indicated that events comprising long periods of low intensity rainfall could lead to redistribution of the wetting profile (due to the nature of the modified Green–Ampt equation) present in the WEPP model and, therefore, could be contributing to underestimation of runoff for larger events. As it has been shown in the previous paragraphs, high intensity rainfall is almost absent in the study area and in this part of the world. Therefore, surface runoff and erosion were mostly due to the low-intensity rainfall with long duration and high rainfall depth.

In general, the WEPP hillslope model simulated fewer runoff events than measured on under the five land use types. Hence, the WEPP hillslope model did not give satisfactory estimates of the surface runoff and the soil loss in the study area.

Table 5 Measured (M) and simulated (S) total runoff (RO) and soil loss (SL) for the period 2003–2005

Land use types	ROM (mm)	ROS (mm)	ROS/ROM (mm)	SL M (kg/ha)	SLS (kg/ha)	SLS/SL M (kg/ha)
LU1	34.6	3.4	0.10	187.1	36	0.20
LU2	65.9	22.3	0.34	794	268	0.34
LU3	82.5	31	0.38	1,283	465	0.37
LU4	55.7	16.8	0.30	334.6	83	0.25
LU5	130.2	65.6	0.50	2,489	1,143	0.46

Table 6 Summary statistics of the WEPP model validation for soil loss according to the land use types

Statistics	LU1	LU2	LU3	LU4	LU5
R^2	0.62	0.59	0.59	0.66	0.75
σ	1.41584	6.71316	9.55895	1.95342	12.7812
b	0.341972	0.345612	0.472434	0.371057	0.487796
Ratio of variances	[3.3586; 8.52341]	[2.46406; 10.1017]	[1.37927; 5.10637]	[3.05035; 7.74113]	[1.98794; 5.04496]

Validation of the artificial neural network

Global networks

In order to develop the network with the best performance, network were trained and simulated with different number of neuron and network architecture (Tables 1, 2, and 3). Table 7 show results obtained for various architectures for the NET1. It shows that the model with eight neurons in the hidden layer and 500 iterations gives the best performances with a minimum average squared error (0.004482) and a high coefficient of determination $R^2 = 0.87$.

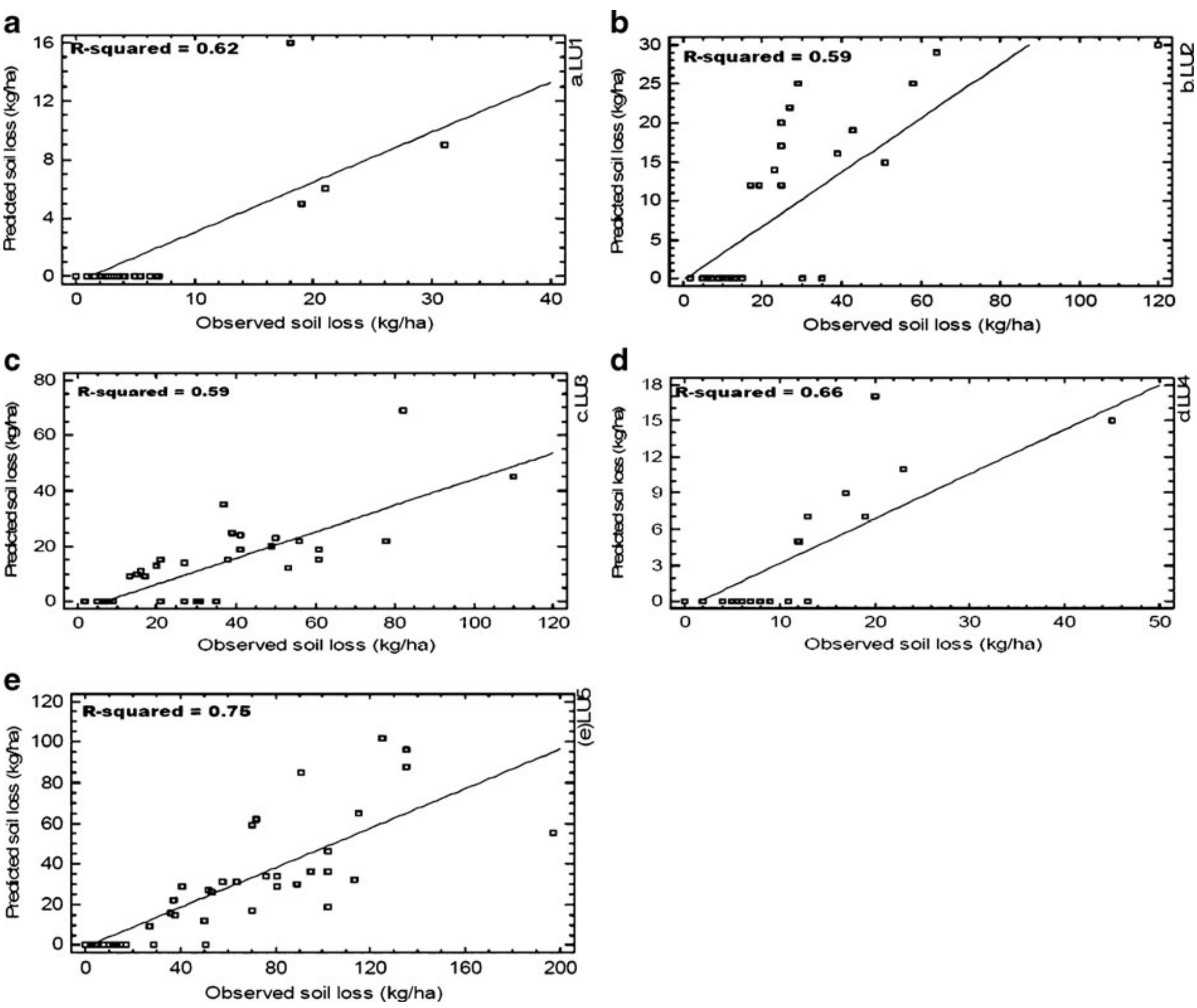


Fig. 6 **a–e** Observed vs. WEPP predicted soil loss under the five land use types

Table 7 Global networks optimal model architecture

Net	Architecture	Iteration	No. initial hidden nodes	No. optimal hidden nodes	ASE training	ASE testing
NET1	10–1–2	500	1	8	0.000765	0.004482
NET2	9–1–1	1,100	1	5	0.001290	0.005825
NET3	10–10–1	800	10	10	0.000370	0.003144

Table 8 Summary statistics of the global NET1 and NET2 of observed versus predicted runoff

Statistics	NET1			NET2		
	Training	Testing	Validation	Training	Testing	Validation
R^2	0.96	0.89	0.80	0.96	0.87	0.86
Slope (b)	1.00336	0.815207	0.815207	0.976707	1.06147	0.85769
Ratio of variances	[0.781541; 1.39999]	[0.491545; 1.12913]	[0.770646; 1.77026]	[0.738611; 1.32097]	[0.851708; 1.95647]	[0.566678; 1.30172]

Table 9 Summary statistics of the global NET1 and NET2 of observed versus predicted soil loss

Statistics	NET1			NET2		
	Training	Testing	Validation	Training	Testing	Validation
R^2	0.98	0.86	0.91	0.98	0.84	0.90
Slope (b)	0.997674	0.997674	1.31079	0.98435	0.966492	1.25401
Ratio of variances	[0.754081; 1.3508]	[0.754081; 1.3508]	[1.23947; 2.8472]	[0.736612; 1.31951]	[0.731971; 1.68142]	[1.14728; 2.63542]

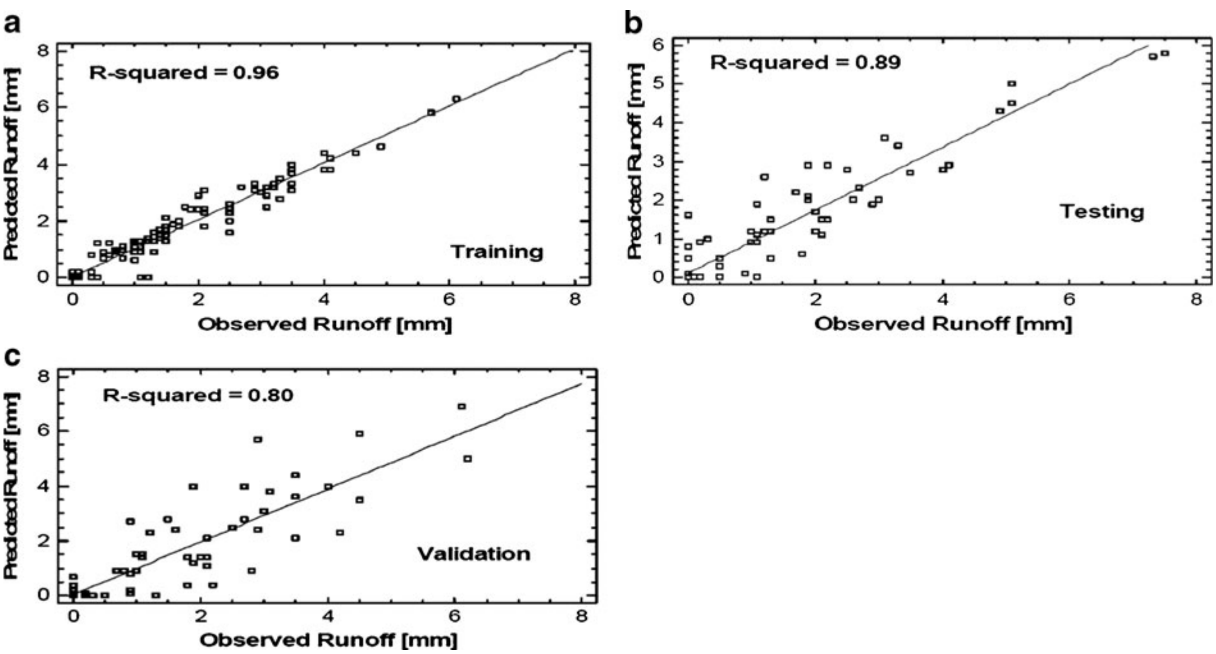


Fig. 7 **a–c** Measured versus predicted runoff values by global NET1 model

Table 8 presents the architecture of the optimal global network model. The network with five neurons in the hidden layer and 1,100 iterations gives best network for NET2. The optimal network for NET3 is obtained with 10 neurons in the hidden layer and 800 iterations.

Table 9 shows the performance of NET1 and NET2 in predicting the runoff. It shows a good agreement between NET1 and NET2 in predicting the runoff at both the training and testing phases. While the NET2 performed better than NET2 at the validation phase.

NET1 and NET2 predicted well the runoff as indicated by the slope of the regression fit equation between the observed and predicated values (Table 9). Figures 7a–c and 8a–c show a comparison between the observed and predicted runoff values for both NET1 and NET2. We observe a very good agreement between these values (Table 9). It can be noted the ratio variances contain the value 1; which confirms that the predicted values are not significantly different from the observed values.

Figures 9a–c and 10a–c show the observed and predicted soil loss values for both NET1 and NET3 for the data of all land use types. Table 10 shows the performance and the efficiency of NET1 and NET3 in predicting the soil loss. It shows that there is no significance difference between NET1 and NET3 in predicting the soil loss at all the phases of the network development.

The slope of the best fit regression equation for all phases of network development for both NET1 and NET3 indicates that the predicted values agree well with the observed values for both the training and testing data set. For the validation phase, a slight over prediction is observed with both models for the soil loss rainfall events.

Table 10 shows the values of the ratio variance between the observed and predicted values of NET1 and NET3. These values indicate that there is no significance difference between the predicted and observed values for all phases of the network, as the ratio contains the value 1.

Results obtained from the global nets (NET1, NET2 and NET3) are significant for both runoff and erosion prediction. Therefore these models performed very well. The phase of training was very well predicted by the three networks, since it contains the largest portion of the dataset (50%).

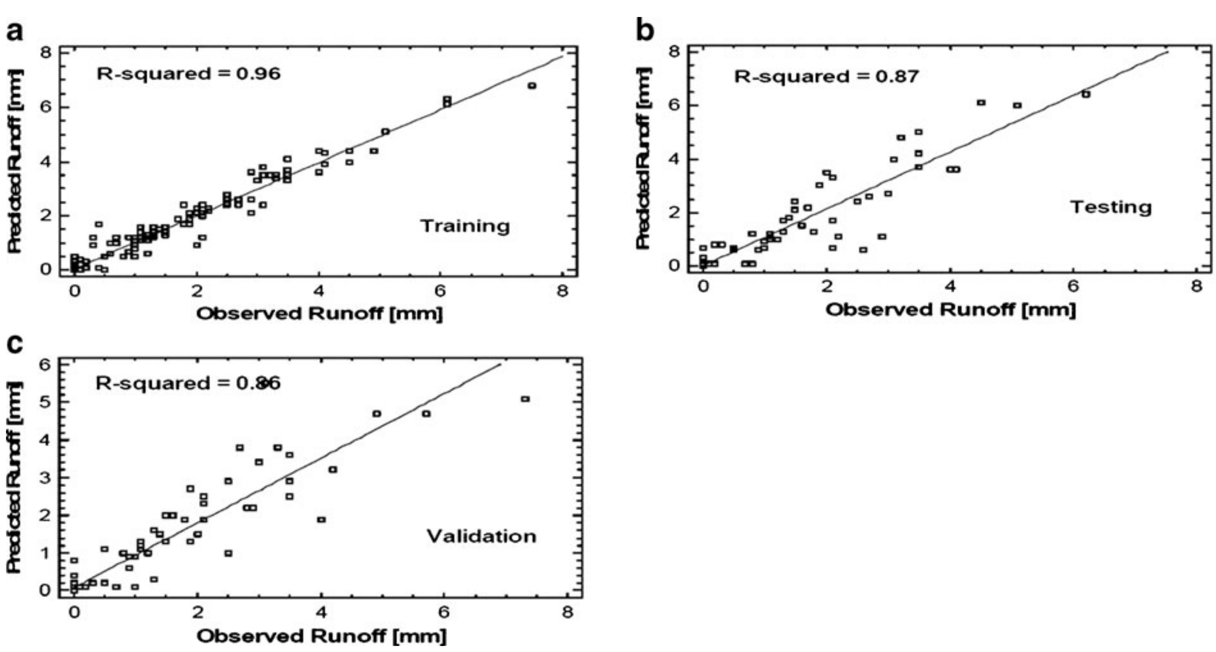


Fig. 8 **a–c** Measured versus predicted runoff values by global NET2 model

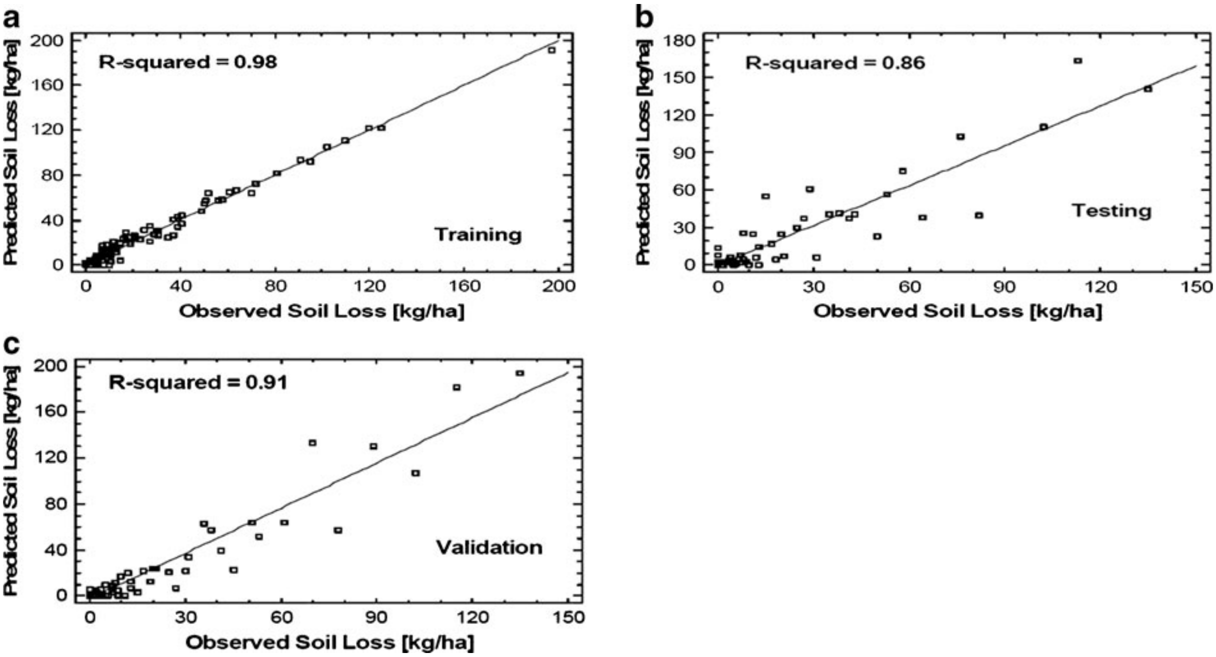


Fig. 9 **a**–**c** Measured versus predicted soil loss by global NET1 model

Individual networks

Table 11 shows the optimal networks for all the individuals Networks type for both the soil loss and runoff. The optimal network was obtained with six neurons in the hidden layer and 600 iterations for NETLU1. The network with two neurons in the hidden layer and 400 iterations

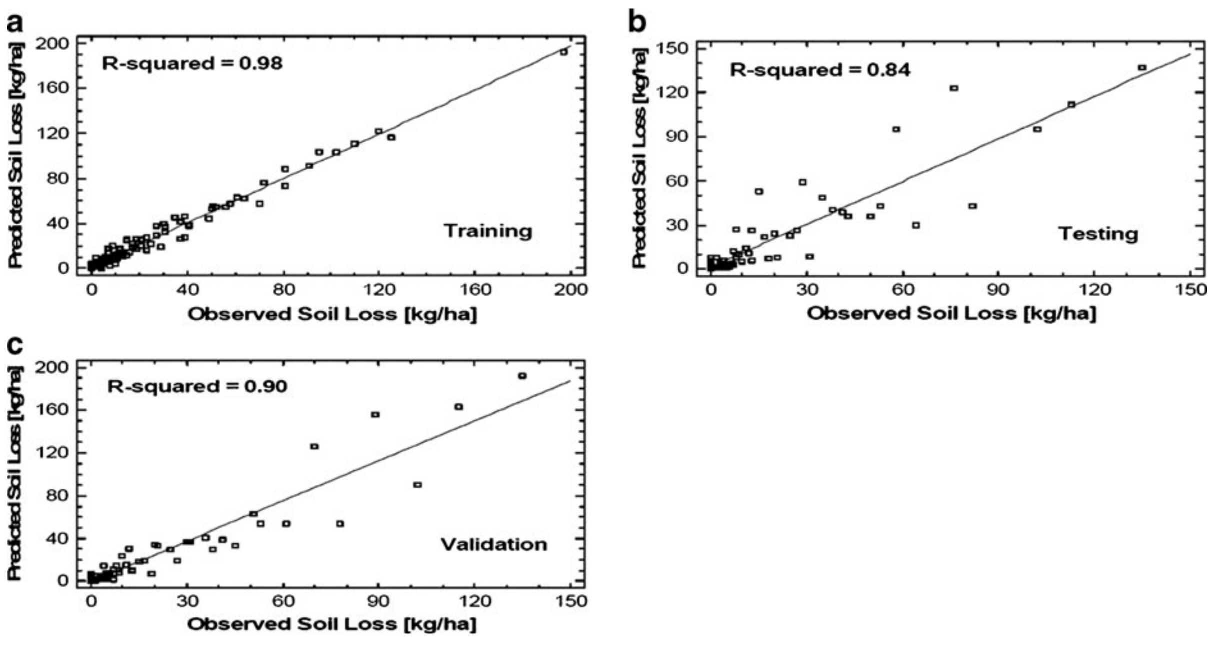


Fig. 10 **a**–**c** Measured versus predicted soil loss by global NET3 model

Table 10 Individuals land use type optimal network architecture

Net	Architecture	Iteration	No. initial hidden nodes	No. optimal hidden nodes	ASE training	ASE testing
NETLU1	6–6–2	600	6	6	0.003298	0.016621
NETLU2	7–1–2	400	1	2	0.003084	0.005998
NETLU3	6–1–2	6,200	1	1	0.006626	0.013180
NETLU4	7–5–2	300	5	5	0.002464	0.012266
NETLU5	7–5–2	500	5	5	0.004959	0.012367

Table 11 Summary statistics of the NETLU1 of observed versus predicted runoff and soil loss

Statistics	Runoff			Soil loss		
	Training	Testing	Validation	Training	Testing	Validation
R^2	0.89	0.88	0.88	0.93	0.91	0.85
Slope (b)	0.909311	0.537736	0.844123	0.907995	0.32561	0.887231
Ratio of variances	[0.478143; 1.80347]	[0.122729; 0.877089]	[0.301512; 2.15477]	[0.453776; 1.71156]	[0.0434178; 0.310287]	[0.345196; 2.46695]

Table 12 Summary statistics of the NETLU2 of observed versus predicted runoff and soil loss

Statistics	Runoff			Soil loss		
	Training	Testing	Validation	Training	Testing	Validation
R^2	0.94	0.90	0.85	0.97	0.83	0.83
Slope (b)	0.972901	0.874377	0.798621	0.935775	1.04021	0.550974
Ratio of variances	[0.516503; 1.94816]	[0.317126; 2.26635]	[0.278626; 1.99121]	[0.465405; 1.75542]	[0.485661; 3.47079]	[0.136158; 0.973058]

Table 13 Summary statistics of the NETLU3 of observed versus predicted runoff and soil loss

Statistics	Runoff			Soil loss		
	Training	Testing	Validation	Training	Testing	Validation
R^2	0.90	0.84	0.79	0.90	0.78	0.80
Slope (b)	0.861514	0.749494	0.820047	0.880115	0.876627	0.803143
Ratio of variances	[0.42525; 1.60396]	[0.249798; 1.78519]	[0.318134; 2.27355]	[0.443516; 1.67286]	[0.368071; 2.63043]	[0.301021; 2.15126]

Table 14 Summary statistics of the NETLU4 of observed versus predicted runoff and soil loss

Statistics	Runoff			Soil loss		
	Training	Testing	Validation	Training	Testing	Validation
R^2	0.95	0.81	0.87	0.96	0.95	0.83
Slope (b)	0.95251	0.745112	0.846105	0.89582	1.35372	1.46257
Ratio of variances	[0.489849; 1.84762]	[0.255402; 1.82524]	[0.309402; 2.21115]	[0.430792; 1.62487]	[0.720889; 5.15186]	[0.969592; 6.92922]

Table 15 Summary statistics of the NETLU5 of observed versus predicted runoff and soil loss

Statistics	Runoff			Soil loss		
	Training	Testing	Validation	Training	Testing	Validation
R^2	0.95	0.82	0.83	0.90	0.83	0.90
Slope (b)	0.984676	1.04225	1.06396	0.932669	0.978406	1.14196
Ratio of variances	[0.52444; 1.97809]	[0.497497; 3.55538]	[0.513283; 3.6682]	[0.494827; 1.8664]	[0.430833; 3.07896]	[0.53881; 3.85062]

gave the best performance for NETLU2. The optimal networks for NETLU4 and NETLU5 were obtained with five neurons in the hidden layers and 300 and 500 iterations, respectively. Finally, the best performance with NETLU3 was obtained with only one neuron in the hidden layer and 6,200 iterations.

The observed and predicted values of runoff and soil loss by NETLU1 are close to each other and there is no significance difference among them in the phase of training and validation as indicated by the ratio of ratio of variances (Table 12). In other hand the predicted values in the testing phase were below the observed values and there was a significance difference between theme despite the high value of the coefficient of determination ($R^2 = 0.88$).

Table 13 shows a good agreement between the observed and predicted values of both the runoff and the soil loss of the NETLU2. As for the erosion, there was no significant difference between the observed and predicted values for both the training and testing phases, while a significant difference was observed between the observed and predicted values for the validation (Table 13). Despite the significant difference between the observed and predicted erosion values in the validation phase, associations between the predicted and observed values were above 72% of the observed values.

The performance NETLU3, NETLU4 and NETLU5 are given in Tables 14 and 15 respectively. We observe a good performance of these models in predicting both the runoff and soil loss for all phases of the model development. This observation is confirmed by the ratio of variances and the slope of the best fit regression line.

The significance difference between the observed and predicted values of NETLU1 in the testing phase for both runoff and erosion, and the significance difference between the observed and predicted values of the soil loss prediction of the NETLU2 could be attributed to the relatively low number of events used in developing the network. However, results obtained with the individuals networks for both runoff and soil loss were better than those obtained with WEEP.

Conclusion

This paper included an investigation of the use of the WEPP and ANN models for simulating both the soil loss and runoff in a semi-arid Mediterranean region. Analyses indicate that the artificial neural network model with a single hidden layer and a feed forward back propagation together with a sufficient amount of observations provides a highly significant output for both the runoff and soil loss. The simulated output for both runoff and soil loss of the global network were good and better than those obtained by the individuals land use networks. The R^2 values for predicting both the soil loss and runoff using the ANN was higher than that obtained with the WEEP model, which confirm the good performances of the ANN model with regard to the WEEP.

Also, the observed and predicted values by ANN were highly significant with no significant different between them. While in the case of WEEP, the predicted values and observed values for both the runoff and soil loss were highly significant. The WEEP model predictions in the Central high land mountains are not very satisfactory. Furthermore, the application of this model for the study area needs detailed and accurate soil, topography and vegetation and land use data. This means that the use of this model requires a considerable work for collecting data, and such a task is time consuming and tedious. The ANN models showed good performances. In addition, it is relatively easy to use. Analyses recommend the use of the ANN for the prediction of both the soil loss and runoff in the Mediterranean region.

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