however have weaker bonds that are mainly created by the cementing effect of its components such as iron oxides, silica, or calcium. Bonds between particles in soils are even weaker and are originated from the cohesion effects of water and the electro- chemical bonds, which exist in clay, and particles of organic matter.

Strength of Bonds in rock material can be weakened by Physical, chemical, and biological weathering. Consequently, weathered materials that are affected by weather effects are more susceptible to detachment forces than unaltered rock. Erosion agents are also able to exert their own detachment forces upon the rock surface or soil through following mechanisms:

Plucking: When trapped water is frozen in cracks and cervices of rocks, it can pull out fragments from rock surface.

Cavitations: observation of rapid water stream has revealed intense erosion due to the surface collapse of air bubbles. In the implosion of the bubble, micro-jet of water is created that travels fast and has great pressure that can produce extreme stress on a very small area of a surface. Cavitations only occurs within high-speed water stream, therefore its effects in nature can be seen only on regions like high waterfalls.

Raindrop impact: the force of a falling raindrop onto soil or weathered rock surface is often sufficient to break weaker particle bonds. Final velocity and mass of the raindrop determine the amount of exerted breaking force.

Abrasion is the excavation of surface particles by materials, which is carried by the erosion agent. Velocity of the moving particles, their mass, and their concentration at the eroding surface are key factors that determine effectiveness of the process. Abrasion can be observed widely In glaciers where the particles are held firmly by ice, it can also occur in the particles held in the erosional mediums of wind and water.

1.5.2 Transport

Once a particle is entrained, if velocity of the medium is high enough to transport the particle it tends to move horizontally. Within the medium type, transport mechanism can occur in four different ways:

The first mechanism is Suspension that can occur in air, water, and ice, when particles are carried by a medium without touching the surface of their origin.

Saltation process, which is only active in air and water, occurs when the particle travels between the surface and the medium in quick continuous cycles. The action of returning to the surface is strong enough to cause entrainment of new particles.

The third one is Traction, which occurs in all erosional medium. In this way, the movement of particles is performed by rolling, sliding, and shuffling along the eroded surface. Solution is a transport mechanism that occurs only in aqueous environments. The process requires that the eroded material dissolve and move alongside the water as individual ions.

Key factors that determine which of abovementioned processes would occur are Particle weight, size, shape, surface configuration, and medium type.

2. The Artificial Neural Networks Approach

2.1 Basic Information

An artificial neuron model is quiet like a biological neuron. It can compile simple mathematical operations and/or can compare two values. An artificial neuron receives input from other neurons or directly from the environment. The connecting path between two neurons is associated with a certain variable weight, which represents the synaptic strength of the connection. The input value to a neuron from another neuron is obtained by multiplying output of connected one by synaptic strength of the connection between them. Then the neuron adds all coming weighted inputs together.

$$X_j = \sum_{i=1}^{m} W_{ij} O_t \tag{1}$$

Where X_j is total value of all the inputs for neuron j while W_{ij} is synaptic strength between neurons i and j, O_t resembles output of neuron i, and m is total number of neurons that send input to neuron j.

Each neuron has a threshold value and squashing function. The squashing function compares the weighted sum of inputs with threshold value of that neuron. If the weighted sum exceeds threshold value then the neuron goes to a higher state, i.e. the output of the neuron becomes 'high'. Different applications require different squashing functions.

In the present work, a back-propagation learning algorithm has been used which necessitates the use of a continuous, differentiable weighting function. Therefore, a sigmoidal squashing function is used as following:

$$O_j = \frac{1}{1 + e^{-\propto(X_j - \theta_j)}} \tag{2}$$

Where the output of neuron J is O_j, X_j is summation of all the weighted sums of the inputs for neuron j, θ_j is threshold value of neuron j, and parameter α controls the slope of the squashing function.

The output of the neuron for a given input can be controlled to a desired value by adjusting the synaptic strengths and threshold values of the neuron. There are various methods to connect several neurons in ANN. Many different types of neural networks have already been developed. The network architecture has to be selected in a way to keep the problem at hand in mind. This work requires training, which has to be carried out by a set of examples in a supervised manner. Therefore, a feed-forward network was found most suitable and brief description of this network is as follows

2.2 Feedforward networks

In feed-forward networks, the neural units are classified into different layers that can be described as one input layer, one or two hidden layers and one output layer of neurons.

A typical feed-forward network is shown in figure 1, as it can be seen from the figure, all of the neurons between two successive layers are in connection with each other, i.e. each neuron of a layer is connected to the corresponding neuron of the neighbouring layer. However, neurons of same layer or those that are not in successive layers are not connected together.

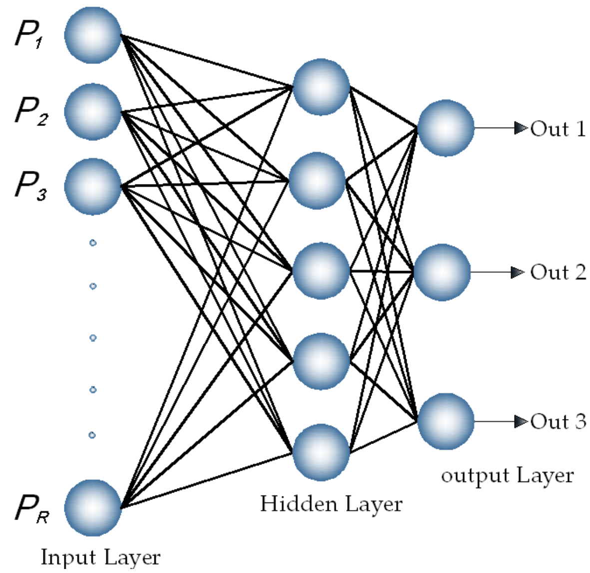

Figure 1 feed forward neural network

Information is received by input layer, and then is passed to output layer via neurons in hidden layers(s). Outcome of the output layer is the prediction of the network for the corresponding input that is supplied at entrance nodes. Behaviour of Each neuron in the network is expressed in Equations (1) and (2). Lack of reliable method for deciding the number of required neural units for a particular problem makes it necessary to use data obtained from previous experiments data and few trial and errors to determine the best configuration of the network.

In feed-forward network, the knowledge in form of synaptic strengths and thresholds is stored in distributed manner. Thus, it can be generalized, i.e. it would be used for situations for which the network has not been trained. Allocation of synaptic strengths and the threshold values are random. Set of training examples is required to train a network with specific knowledge, which includes set of values for the input neurons and corresponding values for the output neurons, and then several of such input–output pairs are made carefully to express all aspects that the network needs to learn. Each training set is the composition of all training examples. At the beginning of the training process, because the synaptic strengths and thresholds are selected randomly the output predicted by the network for a particular input my not match the output supplied in the corresponding training examples. However, the network can predict the output correctly thanks to adjustment features of synaptic strengths and thresholds. As several examples are to be learnt by the network, there must be sufficient number of neural units in the network. Adjustments of the synaptic strengths and thresholds are carried out following a 'learning algorithm' which in this work the back-propagation algorithm has been applied.

2.3 The backpropagation algorithm

Back-propagation algorithm is the generalized form of the least mean square training algorithm for perceptron learning [32-33]. It uses gradient search method to minimize the error function, which is the mean square difference between the desired and the predicted output. The error for *Pth* example is given by:

$$E_p = \sum_j (d_j - O_j)^2 \tag{3}$$

Where d_j is desired output at neuron j and O_j is the actual output of neuron j, as presented in Esq. (1) And (2) the output O_j is the function of synaptic strengths and outputs of the previous layer.

$$O_j = f(\beta_j) = f[\sum_t W_{ij} O_j] \tag{4}$$

The error can be minimized by moving along the steepest descent direction on the error surface

$$\frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial \beta_j}\frac{\partial \beta_j}{\partial W_{ij}} = \frac{\partial E}{\partial \beta_j} O_j = \delta O_j \tag{5}$$

where, δ_j for a neuron is

$$\delta_j = f'(\beta_j) \sum_k \delta_k W_{kj} \tag{6}$$

In the above equation f' is the first order derivative of the function and k resembles a neuron in the layer which situated after the layer containing neuron j. Therefore, for each example the weight matrix can be adjusted recursively.

$$W_{ij}(t+1) = W_{ij}(t) + \eta(\delta_j X_j) \tag{7}$$

In this equation η is an adjustable gain term that controls the rate of convergence. The above operation is repeated for each example and all neurons until a satisfactory convergence is achieved for all of existing examples in the training set.

An artificial neural network simulator is used for the present investigations. A feed-forward network is adopted for training purposes. The error is reduced using a back-propagation algorithm. A sigmoid function is used as the threshold function, which produces an output between 0 and 1. Therefore, the range of input and output is scaled between these two values.

2.4 Performance Criteria

In this study achieving desired optimal network model was accomplished by using Mean Square Error (MSE), Root Mean Square Error (RMSE), correlation of determination (R^2), Correlation Coefficient (R), and Mean Absolute Relative Error(MASE), which are as following:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}(Qt_i - \widehat{Q}t_i)^2}{N} \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(Qt_i - \widehat{Q}t_i)^2}{N}} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Qt_i - \widehat{Q}t_i)^2}{\sum_{i=1}^{N}(Qt_i - \overline{Q}t_i)^2} \tag{10}$$

$$R = \frac{\sum_{i=1}^{N}(Qt_i - \overline{Q}t_i)(\widehat{Q}t_i - \overline{\widehat{Q}t_i})}{\sqrt{\sum_{i=1}^{N}(Qt_i - \overline{Q}t_i)^2 \sum_{i=1}^{N}\sum_{i=1}^{N}(\widehat{Q}t_i - \overline{\widehat{Q}t_i})^2}} \tag{11}$$

$$\mathrm{MARE} = \frac{\sum_{i=1}^{N} |((\widehat{Q}t_i - Qt_i)/Qt_i)|}{N} * 100 \tag{12}$$

where Qt_i and $\widehat{Q}t_i$ denote actual and predicted value of flow and $\overline{Q}t_i$ does the mean of Qt_i values and N is total number of data sets. At first, input and output variable are normalized linearly in the range of 0 and 1, because logistic function has been used (which is bounded between 0.0 and 1.0) the normalization is accomplished using the following equation:

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$$\bar{X} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (13)$$

Here $\overline{X}$ is the original data set and is standardized value of the input; X_{min} and X_{max} is the minimum and maximum of the actual values respectively, in all observations. The main reason for standardizing the data matrix is that the variables are usually measured in different units, by standardizing the variables and recasting them in dimensionless units, the arbitrary effect of similarity between objects will be removed.

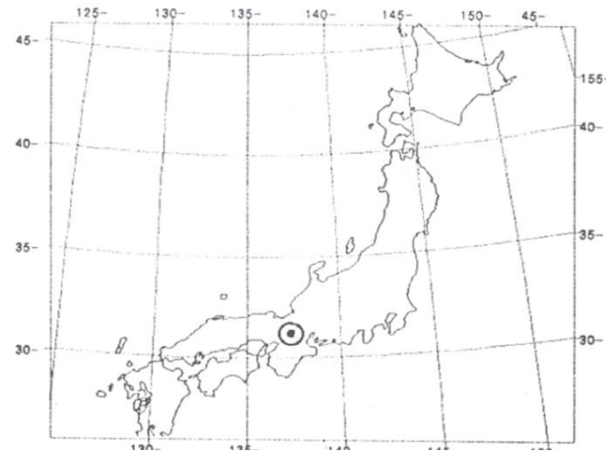

Figure 2 Location of Jakujo Rachidani in the Tanakami area

3. THE STUDY CATCHMENT AND DATABASE

3.1 Study Site:

For the purpose of this work, artificial rainfall test has been performed using an experimental slope, which is completely bare slope located in Jakujo Rachidani of a Tanakami region, in central Japan (35° N, 136° E). The basement area of the experimental slope is 30.1 m2 with slope length of 11.1 m and the mean gradient of 33.6°. An artificial rainfall applied within the area of 18 m2 with the slope length of 4-5 m from the upper reach of the slope [22]. The catchment area is 0.18 ha with mean slope gradient of 34.0 °. Elevation ranges from 358 to 420 metre above sea level and soils are predominantly eroded which consist of decomposed granite without any evident organic layer .Rainfall was measured in a forested catchment adjacent to the Jakujo Rachidani catchment.

The ANN model was trained by outcome data of runoff and rainfall based on each minute data from artificial rainfall test.

3.2 Rainfall Simulator Design:

Artificial rainfall test applied for collecting rainfall runoff data on November10, 2001. Experimental test is provided by spray system including an approximately 2m high tower, two iron pipes equipped with nozzles which spraying upward, a pump, and three water tanks. [34]

The nozzle has an exit pressure of 0.011-0.2Mpa and is supplied by three water storage tank and rainfall intensity can be changed by turning the valve attached to the pump [34].

3.3 Data Collection:

The temporal changes of rainfall intensity were recorded by a tipping bucket type rain gauge, placed on the boundary of the experimental slope. The total rainfall volumes were measured by eight milk packs with total surface area of 7.5×7.5 cm which was placed around the boundary.

Rainfall intensity was measured by the tipping bucket, and then revised by the ratio of the total volume of rainfall recorded by the tipping bucket to the mean value of total rainfall volume collected by the milk packs. Water discharge was collected in a tank whit the capacity of (width×length×height; 40×75×40cm) at the outlet of the experimental slope, and runoff rates were recorded by passing runoff through a tipping bucket from the tank [34].

4. RESULTS AND DISCUSSIONS

One-hour recorded data from artificial rainfall test was used for current study and divided into two categories for training and testing: 70 % for training and 30% for testing phase. The goal was to obtain optimal solution for mean square error (MSE) and maximize correlation coefficient (R) and correlation of determination (R^2) hence the training phase was terminated when the error of testing phase was minimum. Because of high value of error in simulation, logarithmic data has been used in this study in order to decrease error, consequently better results were observed.

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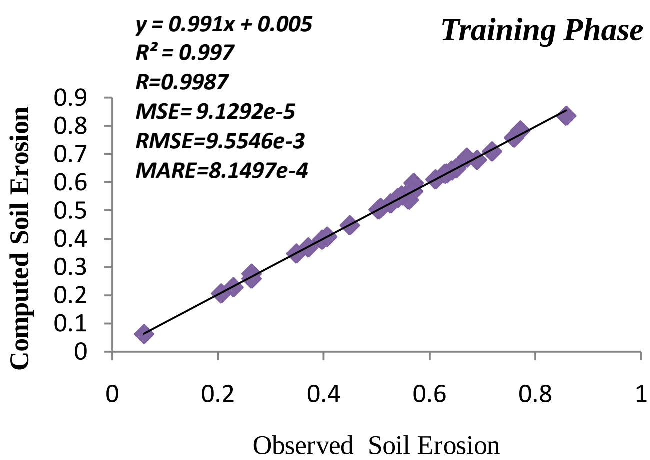

Fig 3 training Phase by ANN model

Fig 3 and 4 show all performance criteria and curve fitting in training and testing Phase .As we can see all these parameters in training phase as better than testing phase because of the large number of data used for training phase. All these parameters should lie down between [0, 1]. Clearly, the optimal value for correlation coefficient and correlation of determination is 1 and in this model, main effort was to obtain higher value for these factors. The Remaining three factors are for errors and optimal value for these ones is zero. For each model, these factors were recorded and compared to each other, which was the best way to choose perfect structure in this study.

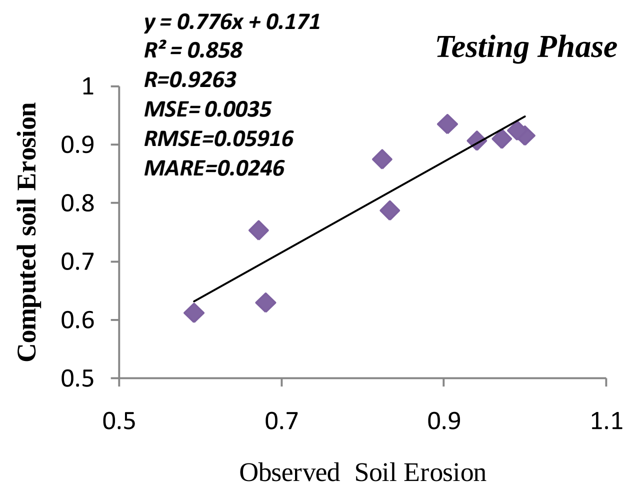

Fig 4 training Phase by ANN model

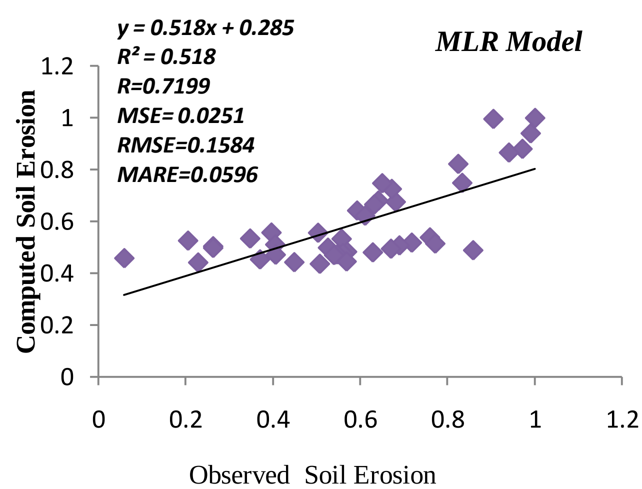

Fig 5 training Phase by MLR model

A traditional method such as multi linear regression has been used in this study as well. Fig 5 shows the fitting curve and performance criteria for this model. These factors demonstrate low ability of MLR compare to ANN in prediction of soil erosion.

Comparison between ANN and MLR methods is presented in fig 6. Better matching between observed soil erosion and predicted data shows the high forecast capability of ANN model compared to MLR model.

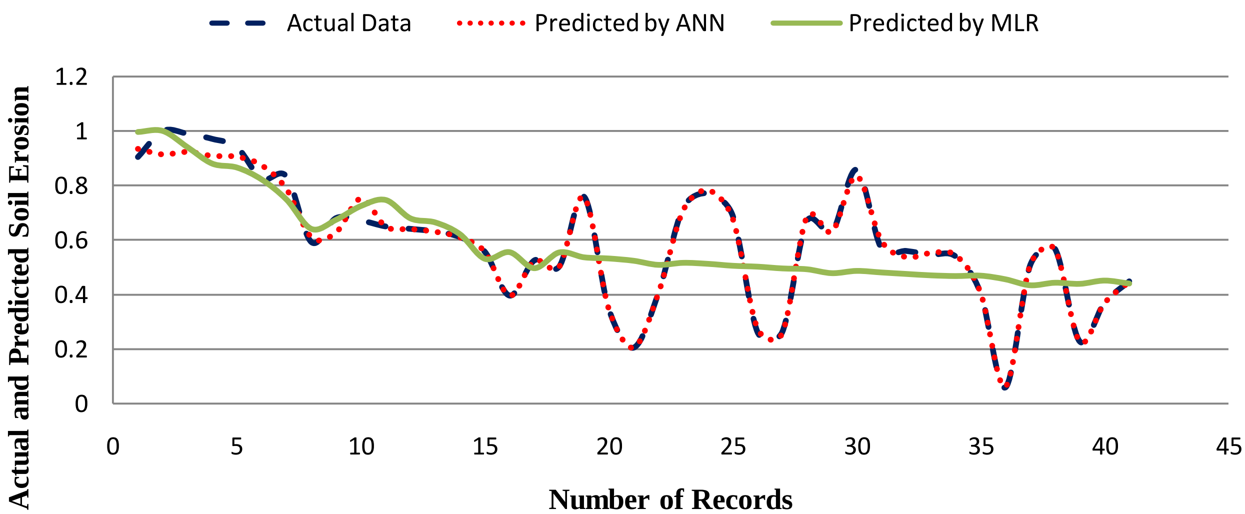

Fig 6 Comparison between ANN and MLR Prediction

Table 1 Comparison between ANN and MLR Prediction

	ANN		*MLR*
	Training	***Testing***	
MSE	***9.13E-05***	***0.0035***	***0.0251***
RMSE	***9.55E-03***	***0.0591***	***0.1584***
R	***0.9987***	***0.9263***	***0.7199***
R^2	***0.997***	***0.858***	***0.518***
MARE	***8.14E-04***	***0.0246***	***0.0596***

All performance criteria are shown in Table 1. Results demonstrate that MSE, RMSE, and MARE are lower for model made by ANN. In contrast, for correlation coefficient(R) and correlation of determination (R^2) the higher value is for ANN model.

5 Conclusion

Overall, the artificial neural network (ANN) based models presented excellent capability in hydrological process modelling. Comparing ANN with traditional models indicates that these models are very powerful tools to handle complicated problems. In this study, outcome data showed that artificial neural networks are very capable of modelling rainfall-runoff relationship in arid and semiarid regions in which rainfall and runoff are very irregular, thus, confirming the general enhancement achieved by using neural networks in many other hydrological fields.

Achieved results and comparative study prove that for the purpose of river run-off prediction the artificial neural network method is more suitable than classical regression model. The ANN approach provides a very accurate tool and solution in water resource studies and management issues.

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