

## Original article

# A Sensitivity Analysis of ANN Pedotransfer Functions for spatial modeling of Soil Cation Exchange Capacity

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## Abstract

The development of models simulating soil processes has increased rapidly in recent years. These models have been developed to improve the understanding of important soil processes and also to act as tools for evaluating agricultural and environmental problems. In this research, an artificial neural network (ANN) model was developed to predict of soil Cation Exchange Capacity (CEC) which was called neural kriging (NK) by easily measurable characteristics of clay and organic carbon. 134 soil samples were collected from different horizons of 34 soil profiles located in the Ziari region, Qazvin province, Iran. The data set was divided into two subsets for calibration (75%) and testing (25%) of the model. In order to evaluate the model, root mean square error (RMSE) and  $R^2$  were used. The value of RMSE and  $R^2$  derived by ANN model were 0.04 and 0.97, respectively. The comparison of RMSE and  $R^2$  for various ANN models showed that the ANN model with three neurons in hidden layer gives better estimates of soil CEC. Sensitivity analysis was also conducted to investigate the effects of various explanatory parameters on the output. The results indicated that CEC variation was more sensitive to clay content than OC variable. For geostatistical analyzing, sampling was done with stratified random method and 34 soil samples from 0 to 15 cm depth were collected with auger within 34 locations. For comparing and evaluation of neural kriging and ordinary kriging methods, cross validation was used by statistical parameters of RMSE and correlation coefficient ( $r$ ) for test data set. The results showed that neural kriging method has the higher correlation coefficient (0.96) and less RMSE (1.22) than ordinary kriging method in predicting and spatial mapping of soil CEC in unsampled areas.

**Keywords:** Artificial Neural Networks, Cross validation, Easily measurable characteristics, Neural Kriging, Sensitivity Analysis

## 1. Introduction

Cation exchange capacity (CEC) is among the most important soil properties that is required in soil databases and is used as an input in soil and environmental models [23, 31].

Cation exchange capacity (CEC) is the amount of negative charge in soil that is available to bind positively charged ions (cations).

Cation exchange capacity is used as a measure of fertility, nutrient retention capacity and the capacity to protect groundwater from cation contamination. Cation exchange capacity buffers fluctuations in nutrient availability and soil pH. Soil components known to contribute to CEC are clay and organic matter and to a lesser extent, silt [52].

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However, soil properties can be highly variable spatially and temporally, and measuring them is both time consuming and expensive. As a result, the most difficult and expensive step towards the process of environmental modeling is the collection of data. The term pedotransfer function (PTF) was coined by Bouma [4] as translating available data (those we have) into useful information (what we need). The most readily available data come from soil survey, such as field morphology, texture, structure and pH. Pedotransfer functions add value to this basic information by translating them into estimates of other more laborious and expensively determined soil properties. These functions fill the gap between the available soil data and the properties which are more useful or required for a particular model or quality assessment.

Although CEC can be measured directly, its measurement is especially difficult and expensive in the Aridisols of Iran because of the large amounts of calcium carbonate and gypsum [6, 15]. Various PTFs have been developed to estimate CEC from basic physical and chemical soil properties [2, 5, 31, 37]. In most of these models, CEC is assumed to be a linear function of soil organic matter and clay content [5, 37]. Results show that greater than 50% of the variation in CEC could be explained by the variation in clay and organic carbon content for several New Jersey soils [12], for some Philippine soils [48], and for four soils in Mexico [2]. Only a small improvement was obtained by adding pH to the model for four Mexican soils [2]. In B horizons of a toposequence, the amount of fine clay was shown to explain a larger percent of the variation in CEC than the total clay content [59].

Bell and van Keulen [2] studied Mexico soils and proposed an equation to predict soil CEC by some independent variables such as clay, organic carbon and pH. In their equation, 96% of soil CEC variations were explained by clay, organic carbon and pH. Also, Krogh *et al.* [27] suggested an equation based on silt, clay, organic carbon and pH which explained 90% of soil CEC variation. Amini *et al.* [1] estimated the cation exchange capacity in the central of Iran using soil organic matter and clay contents. They used the ANN and five experimental models that were on the basis of regression methods for their predictions. They showed that a neural network PTF with eight hidden neurons was able to predict CEC better than the regression PTFs. Also the ANN model significantly improved the accuracy of the prediction by up to 25%. They concluded that network models are in general more suitable for capturing the non-linearity of the relationship between variables. Jain and Kumar [21] indicated that the ANN technique can be successfully

employed for the purpose of calibration of infiltration equations. They had also found that the ANNs are capable of performing very well in situations of limited data availability.

Saffari *et al.* [47] developed and evaluated two different ANN models for prediction of spatial variability of some chemical properties in Fars province, Iran. They reported that multiple hidden layers ANN model with the structure of 2-4-5-1 had better performance for estimation of some chemical properties than single hidden layer ANN model with the structure of 2-20-1 in the studied area. Garcet *et al.* [17] compared multidimensional kriging and ANN for nitrate leaching modeling in Brusselean aquifer in Belgium. The comparison between the two tested metamodells -multidimensional kriging and radial basis functions neural networks- showed that, for the particular case of modelling nitrate leaching from agricultural origin in the area of the Brusselean aquifer in Belgium, multidimensional kriging is the best method. Chowdhury *et al.* [9] compared ordinary kriging and artificial neural network for spatial mapping of arsenic contamination of groundwater in Bangladesh. They founded that the use of a highly nonlinear pattern learning technique in the form of an artificial neural network (ANN) can yield more accurate results under the same set of constraints when compared to the ordinary kriging method. Kholghi and Hosseini [24] estimated the aquifer transmissivity using kriging, artificial neural network and neuro-fuzzy models. The results indicated that neuro-fuzzy model was more efficient to estimate the transmissivity in comparison with the ANN and kriging models.

Hence, the present study was carried out with objectives to (1) developing Pedotransfer Functions (PTFs) for estimating soil CEC using Artificial Neural Networks (ANNs) by easily measurable characteristics of clay and organic carbon (2) a sensitivity analysis of ANN Pedotransfer Functions and (3) comparing neural kriging and ordinary Kriging methods in spatial mapping of soil CEC in Ziaran region, Qazvin province, Iran.

## 2. Material and method

### Site description

The land investigated in the research is located in Ziaran (Qazvin province in Iran) which has an area about 5121 hectares; between latitudes of 35°58' and 36°4' N and longitudes of 50°24' and 50°27' E. The average, minimum and maximum heights points of Ziaran district are 1204, 1139 and 1269 meters above the sea level, respectively.

Figure 1 shows the study area in Iran. The soil moisture and temperature regimes of the region by means of Newhall software are Weak Aridic and

#### Data collection and soil sample analysis

After preliminary studies of topographic maps (1:25000), using GPS, studying location was appointed. 134 soil samples were collected from different horizons of 34 soil profiles located in the Ziari region, Qazvin province, Iran. Measured soil parameters included texture (determined using Bouyoucos hydrometer method), organic carbon (OC) was determined using Walkley-Black method [39], and CEC (cation exchange capacity in Cmolc kg<sup>-1</sup> soil) determined by the method of Bower [55]. For geostatistical analyzing, sampling was done with stratified random method and 34 soil samples from 0 to 15 cm depth were collected with auger within 34 locations in the Ziari region.

#### Artificial neural network

Neural classifiers can deal with numerous multivariable nonlinear problems, for which an accurate analytical solution is difficult to obtain [43]. An artificial neural network is a highly interconnected network of many simple processing units called neurons, which are analogous to the biological neurons in the human brain. Artificial neural networks are becoming a common tool for modeling complex "input-output" dependencies [32,34]. The advantage of ANN is their ability to mimic the behavior of complex systems by varying the strength of the influence of network components to each other and by varying the structure of the interconnections among components.

Neurons having similar characteristics in an ANN are arranged in groups called layers. The neurons in one layer are connected to those in the adjacent layers, but not to those in the same layer. The strength of connection between the two neurons in adjacent layers is represented by what is known as a "connection strength" or "weight". An ANN normally consists of three layers, an input layer, a hidden layer, and an output layer. A type of ANN known as multilayer perceptron (MLP), which uses a back-propagation training algorithm, is usually used for generating PTFs [1, 37, 38, 51]. This network uses neurons whose output is a function of a weighted sum of the inputs. In a feed forward network, the weighted connections feed activations only in the forward direction from an input layer to the output layer. Feed-forward ANNs are most often used to map input-output relationships [32]. Feed-forward ANNs are organized in layers that contain neurons (also called nodes). The number of neurons in input and output layers corresponds to the number

Thermic, respectively. Based on soil taxonomy [38], this region has soils in Entisols and Aridisols orders.

of input and output variables,  $J$  and  $L$ , respectively. The number of "hidden" neurons,  $K$ , can be chosen freely, and determines the complexity that can be modeled. The  $J$  inputs  $X_1$  through  $X_J$  normally do not undergo any operation and are all connected to the  $K$  hidden neurons. At each hidden neuron  $k = 1$  through  $K$  each input  $X_j$  is weighted, summed and biased (with a value  $b$ ) to produce a single value,  $S_k$ :

$$S_k = \sum_{j=0}^J (w_{jk} X_j) + b_k \quad (1)$$

Each neuron has its own values of  $w_i$  and  $b$ , the coefficients in each layer are situated in the matrix and vector elements  $w_{jk}$  and  $b_k$ ; respectively. Similar operations occur at the output nodes 1 through  $L$ , with matrices and vectors with elements  $w_{kl}$  and  $b_l$ ; respectively. The values  $S_k$  in hidden and output nodes are operated on by an activation or transfer function. The activation function is usually a monotonic function that can be easily evaluated [19]. Most commonly the sigmoid function is used for neurons in hidden and output layers (eq.2), thus limiting the output  $Y_1$  through  $Y_L$  between 0 and 1. However, linear output functions are sometimes used for output layers to extend the output range to, theoretically, plus and minus infinity (eq.3). Other activation functions such as hyperbolic tangents can also be used [10].

$$\phi(S_k) = \frac{1}{1 + \exp(-S_k)} \quad (2)$$

$$H(S_k) = S_k \quad (3)$$

The structure of a feed-forward ANN is shown in Fig. 1. This ANN is a popular neural network which known as the back propagation algorithm introduced by Karaca and Ozkaya [22]. This ANN had  $k$  input and one output parameters. They used this ANN for accurate modeling of the leachate flow-rate. They also reported that the input parameters, number of neurons at the hidden and output layer should be determined according to currently gathered data. Moreover, an important step in developing an ANN model is the training of its weight matrix. The weights are initialized randomly between suitable ranges, and then updated using certain training mechanism [38, 42, 51].

In the feed-forward networks, error minimization can be obtained by a number of procedures including Gradient Descent (GD), Levenberg-Marquardt (LM) and Conjugate

Gradient (CG). BP uses a gradient descent (GD) technique which is very stable when a small learning rate is used, but has slow convergence properties [41].

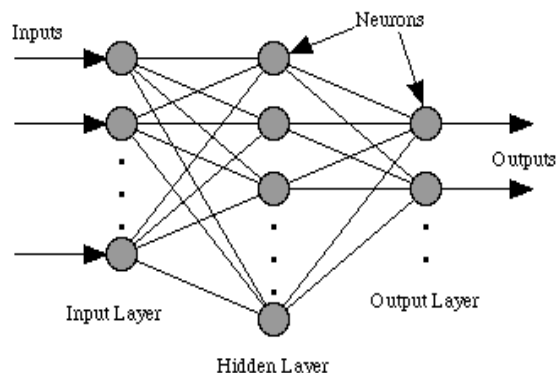


Figure 1. Structure of feed-forward ANN

Several methods for speeding up BP have been used including adding a momentum term or using a variable learning rate. In this study, LM algorithm in the sense that a momentum term is used to speeding up learning and stabilizing convergence is used. In this study, the training process was performed by NeuroSolutions 5.0 software which includes a number of training algorithms including the back propagation training algorithm.

### Performance criteria

The performance of the models was evaluated by a set of test data using the root mean square error (RMSE) and the coefficient of determination ( $R^2$ ) between predicted and measured values. The RMSE is a measure of accuracy and reliability for calibration and test data sets [60], and is defined as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^n (z_o - z_p)^2} \quad (4)$$

Where:  $Z_o$  is observed value,  $Z_p$  is predicted value,  $n$  is number of samples.

### Sensitivity analysis

A sensitivity analysis was performed on the chosen ANN's so that a better understanding of the relative importance of each input on the output could be examined. Thus, sensitivity analysis was carried out to investigate the dynamic behavior of input variables. This was done by imposing steps changes to various inputs and observing their effects on the network output. These responses were used

as guides to select appropriate input variables that are suitable for model development.

### Spatial prediction methods

#### Ordinary Kriging (OK) and Neural Kriging (NK)

Optimizing spatial sampling scheme to reduce sampling density and estimation of unsampling values can save time and costs [16, 30]. However, its effectiveness relies on the accuracy of the spatial interpolation used to define the spatial variability. Multivariate techniques such as geostatistics and artificial neural network (ANN) have been widely used as estimation tools. Geostatistics provides descriptive tools such as kriging to directly implements the prediction of an attribute at an unsampled location according to known data points within a local neighborhood surrounding [13]. ANN has the ability to model extremely non-linear and complicated relationships between a set of inputs, and are operated by using the available input and output responses without considering inherent system parameters [49]. It can be used as an alternative to predict regionalized variables (RV) which are functions on geographic locations [14,20]. Many comparisons of various interpolation techniques have been made in respect to different data sets used, different mathematical procedures and different input parameters [3,46]. Moreover, very few studies compare the performance of OK and ANN methods simultaneously [45]. However, ANN only allows the RV estimation, but not the predictor variance, which is possible with kriging [26,45]. In some applications ANN is coupled with kriging estimation, which was called neural kriging (NK) by Rizzo and Dougherty [45]. The term of neural kriging (NK) is used by some researchers [7,45] for simply defining a neural model of the regionalized variable; whereas other authors like Koike et al. [26] use this term when they adapt the NNs to the problem by changing their architecture in order to take into account, implicitly or explicitly, the spatial data correlation. If ANNs are coupled with kriging, they can estimate the data nonlinear trend better than the universal kriging (UK) estimator. After this neural de-trending, a simpler technique, like ordinary kriging (OK), can be used [7]. In the present study, our focus was on the investigation of two spatial mapping based on distinct spatial interpolation methodologies. The first mapping tool is the commonly known geostatistical ordinary kriging (OK) technique; based on the linear paradigm of mapping. The second mapping tool is the ANN based on the non-linear paradigm of mapping. For each mapping technique, the goal was to spatially interpolate the soil CEC content in unsampled areas. We used cross-

validation to validate the accuracy of interpolation algorithms and examine the difference between the measured values and the predicted values using root mean square error (RMSE) and correlation coefficient (r) for test data set. RMSE and correlation coefficient indicate degree of agreement between measured and predicted values. Detailed descriptions and definitions of these model performance parameters are given by Robinson & Metternicht [45] and Farifteh et al. [14]. Conventional statistical analyses were conducted using the software package SPSS 15.0 for Windows (SPSS Inc., MatLabR, USA). Geostatistical analyses and mapping were performed by using ArcGIS 9.2 software package (Environmental Systems Research Institute, Redlands, CA).

### 3. Results and Discussions

#### Data summary statistics

Data summary of training and testing sets are presented in tables 1 and 2, respectively. Data subdivided into two sets: 25% of the data for testing and the remaining 75% of the data were used for training or calibrating. Some soil parameters including clay and organic carbon were input data for prediction of CEC. However, clay and organic carbon were considered as inputs for prediction of cation exchange capacity. Amini et al. [1] stated that CEC has high correlation with these inputs. They found that inputs like sand and silt can not improve accuracy of prediction of CEC.

Table 1. Statistics of training data set for cation exchange capacity (n=100)

Training set	Soil parameter	Min	Max	Mean	Std. Dev.	Skewness
	CEC (Cmol <sup>+</sup> Kg <sup>-1</sup> )	10.67	21.39	16.91	2.59	-0.53
	Clay (%)	6.56	69.90	30.08	15.19	0.46
	OC (%)	0.09	0.79	0.41	0.16	-0.24

Table 2. Statistics of testing data set for cation exchange capacity (n=34)

Testing set	Soil parameter	Min	Max	Mean	Std. Dev.	Skewness
	CEC (Cmol <sup>+</sup> Kg <sup>-1</sup> )	12.83	20.10	16.80	1.94	-0.41
	Clay (%)	10.56	52.50	27.68	11.10	0.42
	OC (%)	0.40	1.33	0.77	0.19	-0.21

Simple linear correlation coefficients (r) between CEC and independent variables were also calculated (table 3). As table 3 illustrates correlations between OC and CEC and between clay and CEC were positive and highly significant. For example the correlation coefficients between CEC and clay content ( $r = 0.95^{**}$ ) is more than between CEC and OC content ( $r = 0.59^{*}$ ). Positive

correlation between CEC, OC and clay content is related to existence of negative charges on these properties [2, 31, 40]. However with regarding to these correlation coefficients, both of them are suitable for developing PTFs for prediction of CEC in soils of Ziara region.

Table 3. Simple linear correlation coefficients (r) between CEC and independent variables

	CEC (Cmol <sup>+</sup> Kg <sup>-1</sup> )	Clay (%)	OC (%)
CEC (Cmol <sup>+</sup> Kg <sup>-1</sup> )	1		
Clay (%)	0.95 <sup>**</sup>	1	
OC (%)	0.59 <sup>*</sup>	0.35 <sup>*</sup>	1

\* Correlation is significant at the 0.05 level

\*\* Correlation is significant at the 0.01 level

#### Developing PTFs using Artificial Neural Networks

In the present study for predicting soil CEC we did not increase the input data for constructing artificial neural network. Because according to findings of Lake et al. [29] and Amini et al. [1] increasing the number of inputs will decrease the accuracy of the estimations. For example for predicting a soil characteristics if just one types of the input data have low correlation coefficients with output data, the accuracy of the model will automatically decrease. Therefore the ANN input layer was consisted of two data in this model were consisted of exploratory variables, namely, clay and OC After randomizing and splitting of data set into training and testing data, various ANN structures of the topology 2-k-1, i.e., networks having two neurons in the input layer, one hidden layer with different number or neuron ( $k = 1, 2, \dots, 10$ ), and one neuron (CEC) as the output layer were designed. The optimum structures of network were decided by means of  $R^2$  and RMSE criteria. The RMSE values for various k (numbers of neurons in the hidden layer) related to studied soil parameter is presented in the fig. 2.

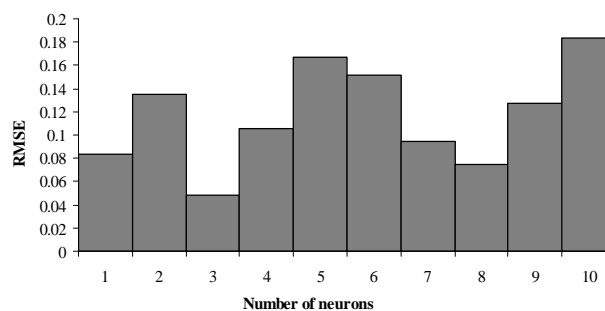


Figure 2. RMSE values for 1-10 neurons in hidden layer (cation exchange capacity)

Amini et al. [1] found that the neural network-based models provided more reliable predictions than the regression-based PTFs. Schaap et al. [51] confirmed applicability of ANNs and concluded that accuracy of these models depend on number of inputs. Koekkoek and Booltink [25] found that ANN performed slightly better, but the differences were not significant. One of the advantages of neural networks compared to traditional regression PTFs is that they do not require a priori regression model, which relates input and output data and in general is difficult because these models are not known [50]. The reason of this superior efficiency of ANNs models compare with the basic regression equations is probably because; the PTFs that have derived from various areas have the suitable for capturing the non-linearity of the relationship between variables. On the other hand, according to the hypothesis of Schaap et al. [51], for designing of a neural network we do not need to a special equation. They also believe that with creation a suitable equation between input and output data we are able to achieve to the best results. Also, due to the occurring of nonlinear equations between dependent variables and predicting variables, the neural network have the better efficiency compared with the basic regression equations. Pachepsky et al. [42] investigated the accuracy of artificial neural network and analyzed the regression method using correlation coefficient and the root mean square error. They reported that the neural network is able to predict the easily measurable soil parameters with more accuracy and less error. The similar results have reported by the Tamari et al. [56] as well.

They found that using artificial neural network leads to less RMSE values than the multivariable linear regression. They also reported that the neural network has not better efficiency than linear regression models in occasion of high stability of data. However, the high accuracy of data leads to more efficiency of neural network and also, shows the proper selection of testing and training data. Analysis of the ANN parameters suggested that more input variables were necessary to improve the prediction of soil parameters [35, 56].

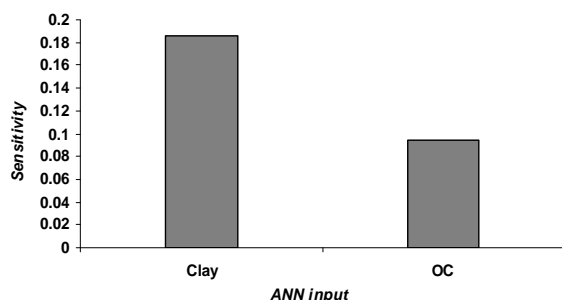


Figure 3. Sensitivity analysis of ANN inputs on CEC

### Sensitivity analysis

In order to assess the predictive ability and validity of the developed ANN model, sensitivity analysis was conducted using the best single output network. The robustness and sensitivity of the model were determined by examining and comparing the outputs produced during the testing stage with the calculated values [62]. This was done by measuring the mean rate of change of output when a single input was changed by some relatively small amount (0.001). The ANN model was trained by removing one explanatory parameter at a time while not changing any of another item for every pattern. Result of sensitivity analysis for CEC is shown in fig 3.

The most meaningful explanatory parameter for the ANN models was clay content (%) for prediction of soil CEC. The results indicated that CEC variation was more sensitive to clay content (0.1854) than OC variable (0.0938). The relationship between clay content (%) and CEC can be highly variable because different clay minerals have different CEC values. In addition, the relative proportion of pH-dependant and permanent CEC varies among clay minerals [36, 44]. Moreover, the correlation coefficients between CEC and clay content ( $r = 0.95^{**}$ ) is more than between CEC and OC content ( $r = 0.59^{*}$ ).

### Geostatistical analysis

A summary of statistical data related to soil CECs (CEC and CEC (ANN)) are presented in Table 4. We investigated the normality condition of the data. Their normality was tested by Kolmogorov-Smirnov method ( $P$  - value > 0.05). With due attention to the levels of skewness for soil CECs, these parameters were normal. The first step in using of kriging method is to investigation of the presence of spatial structure among the data by variogram analysis. Geostatistical methods were developing to create mathematical models of spatial correlation structures with a variogram as the quantitative measure of spatial correlation.

Table 4. Results of statistical analysis on studied soil CECs

Soil CEC (Cmol <sup>c</sup> Kg <sup>-1</sup> )	Min	Max	Mean	Std. Dev.	Skewness	CV <sup>a)</sup> (%)
CEC	12.83	20.10	16.80	1.94	-0.41	11.54
CEC (ANN) <sup>b)</sup>	12.68	20.08	16.82	1.97	-0.46	11.71

<sup>a)</sup> CV = Coefficient of Variation

<sup>b)</sup> CEC (ANN) = CEC predicted by ANN method

The experimental variogram measures the average degree of dissimilarity between unsampled values and a nearby data value [11] and thus can depict autocorrelation at various distances. The

value of the experimental variogram for a separation distance of  $h$  (referred to as the lag) is half the average squared difference between the value at  $z(x_i)$  and the value at  $z(x_i+h)$  [29, 46]:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i + h) - z(x_i)]^2 \quad (5)$$

Where:  $N(h)$  is the number of data pairs within a given class of distance and direction. If the values at  $z(x_i)$  and  $z(x_i+h)$  are auto correlated the result of Eq.(5) will be small, relative to an uncorrelated pair of points. From analysis of the experimental variogram, a suitable model is then fitted, usually by weighted least squares, and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure. The kriging estimation variances are independent of the value being estimated and are related only to the spatial arrangement of the sample data and to the model variogram [58]. For investigating correlation of the soil CEC, the appropriate variogram must be determined. The best fits were obtained by gaussian models [24] plus a nugget effect and less RSS value (table 5). A non-linear model (Gaussian) was applied, as follow [24]:

$$\gamma(h) = \begin{cases} C_0 + C \left( 1 - \exp\left(-\frac{h^2}{a^2}\right) \right), & h \leq a \\ C, & h > a \end{cases} \quad (6)$$

Where: the  $C_0$  is the nugget, the  $C_0+C$  is the sill,  $a$  is the range and  $h$  = lag distance.

Nugget effect, which is obtained by extrapolating the behaviour of experimental semivariogram to the origin ( $h=0$ ), may be due to small scale variation or measurement errors [8, 18, 58, 61]. The gaussian model indicates the spatial continuity of underlying variable. Another parameter which is a measure of the spatial continuity is the ratio of nugget to sill ( $C_0/C+C_0$ ). This ratio can be regarded as a criterion for classifying the spatial continuity of the variables [8]. If this ratio is less than 25% the spatial continuity is strong, between 25% and 75% the variable has a moderate spatial continuity, and when the ratio is more than 75% weak spatial continuity is suspected [53]. In this study, the ratio of nugget to sill in the semivariograms varied from 4.11% to 7.83% for soil CECs (table 5), which indicates a strong spatial continuity for soil CECs.

Table 5. Best-fitted variogram models of soil CECs and their parameters

Soil CEC (Cmol <sup>+</sup> Kg <sup>-1</sup> )	Model	Nugget (C <sub>0</sub> )	Sill (C+ C <sub>0</sub> )	Range effect (km)	C <sub>0</sub> /C+C <sub>0</sub> (%)	RSS (Cmol <sup>+</sup> Kg <sup>-1</sup> )
CEC	Gaussian	0.94	22.87	24.6	4.11	6.95
CEC (ANN) <sup>a)</sup>	Gaussian	0.65	8.30	17.02	7.83	4.26

<sup>a)</sup> CEC (ANN) = CEC predicted by ANN method

As shown in table 5, soil CECs has strong spatial structure ( $C_0/C + C_0 < 25\%$ ). The range effect for CEC is approximately 24.6 km, and this parameter related to CEC (ANN) is about 17.02 km as well. The RSS value for CEC (ANN) is less than another soil CEC. After modeling of variogram, kriging method was used for prediction of spatial distribution of the soil CECs.

For evaluation of the soil CECs mentioned above, RMSE and correlation coefficient ( $r$ ) were used. According to table 6, ANN-kriging (Neural Kriging) method was expected to be superior to CEC-kriging method (CEC predicted by kriging) for estimating of soil CEC. Sitharam et al. [54] investigated spatial variability of rock depth in Bangalore using geostatistical, neural network and support vector machine (SVM) models.

Comparison between ANN, ordinary kriging and SVM models developed with the available data indicated that ANN model had superior to ordinary

kriging and SVM models developed with the available data for predicting reduced level of rock values in the subsurface of Bangalore.

Zheng et al. [63] studied spatial estimation of soil moisture and salinity with neural kriging in Northwest China. They compared ordinary kriging (OK) and back-propagation neural network (BPNN) with 107 measurements of volumetric soil water content (SWC) and electrical conductivity (EC) for soil profiles (0 - 30 cm). The results showed that BPNN method predicted slightly better accurate soil moisture than that of OK.

In addition, BPNN performed much better in EC prediction with higher model efficiency factor than that of OK.

Moreover, a novel neural kriging (NK) resulting from the integration of neural network (NN) and ordinary kriging (OK) techniques was developed through a geographical information system (GIS) environment for obtaining trend maps

of soil moisture and EC. Comparing with OK, NK gives better spatial estimations for its great advantage of establishing spatial nonlinear relationships through training directly on the data without building any complicated mathematical models and making assumptions on spatial variations.

Table 6. Results of the interpolation standard error for estimation of soil CECs

Soil CEC (Cmol <sup>c</sup> Kg <sup>-1</sup> )	RMSE (Cmol <sup>c</sup> Kg <sup>-1</sup> )	Correlation coefficient between observed and predicted value (r)
CEC	1.53	0.92*
CEC (ANN) <sup>a)</sup>	1.22	0.96*

\*Correlation is significant at the 0.05 level

<sup>a)</sup> CEC (ANN) = CEC predicted by ANN method

The scatter plot of the measured against predicted soil CEC for kriging methods are given in

fig 4. So that according to this diagrams, the best fitted line has the angle of near to 45° that shows the high accuracy of estimation by the ANN-kriging method. Finally, the maps of spatial distribution of soil CECs were prepared. Fig 5 shows spatial variability maps of soil CECs and fig 6 shows spatial variability of interpolated standard error maps for soil CECs using kriging methods. So that with decreasing in elevation and increasing in clay content and changing in soil texture (becomes finer) and land forms, soil morphology and soil physico-chemical properties have changed. In the lands with low slope, soil drainage has been poorly and soil pH is alkaline.

These soils usually have the accumulation of salts and led to the formation of smectite minerals. These factors increased CEC from northern to Southern region.

The kriged maps also showed them.

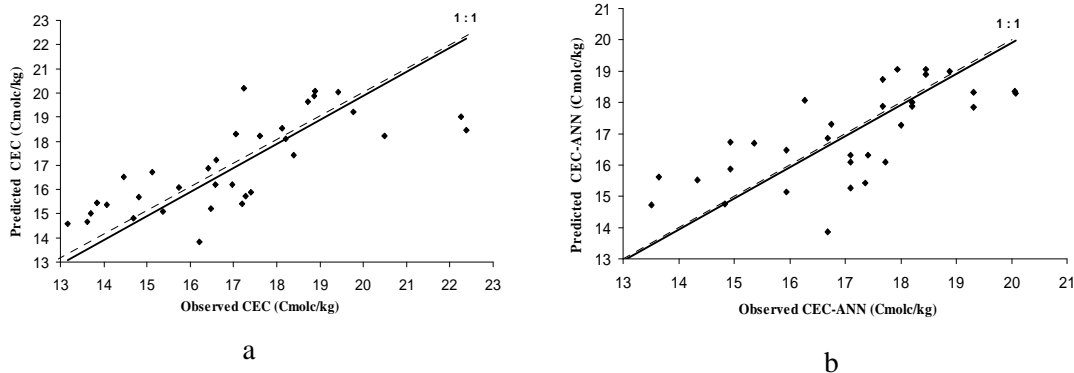


Figure 4. The scatter plot of the measured versus predicted soil CEC in: (a) CEC (kriging), (b) ANN-kriging

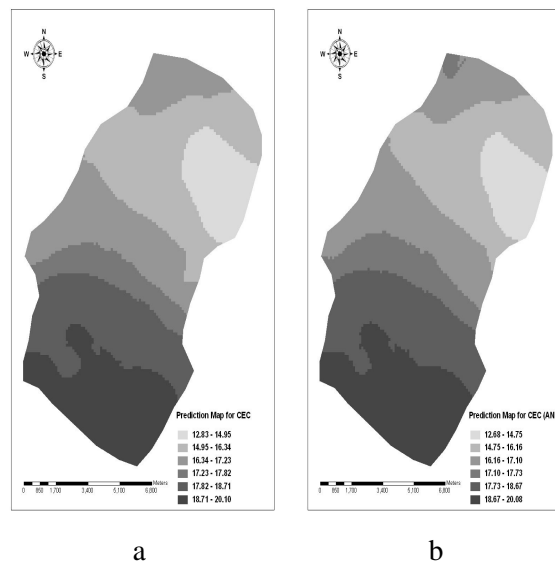


Figure 5. Map of spatial variability of soil CEC using: (a) CEC (kriging), (b) ANN-kriging



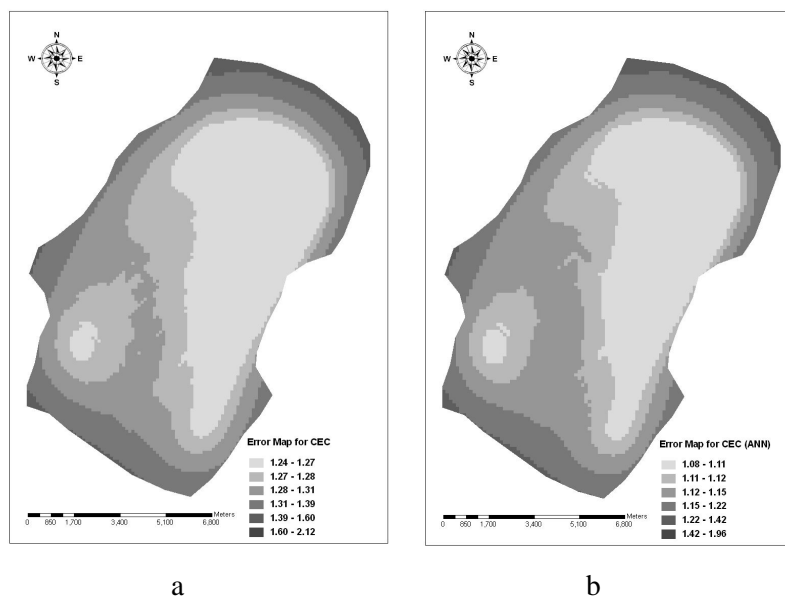


Figure 6. Map of spatial variability of interpolated standard error for estimation of soil CEC in: (a) CEC(kriging), (b) ANN-kriging

#### 4. Conclusions

In this study, neural network model (feed-forward back-propagation network) was employed to develop a pedotransfer function for predicting soil CEC by using available soil properties. This network was consisted of one hidden layer, a sigmoid activation function in hidden layer, and a linear activation function in output layer and Levenberg-Marquardt training algorithm used due to efficiency, simplicity and high speed. For predicting the soil property by means of PTFs, the input data were consisted of clay and OC contents for CEC. The performance of the neural network model was evaluated using a test data set. The comparison of RMSE and  $R^2$  for various ANN models showed that the ANN model with three neurons in hidden layer gives better estimates of soil CEC. The result of sensitivity analysis showed that the most meaningful explanatory parameter for the ANN models was clay content (%) for prediction of soil CEC. The key aim of the work is to contribute to the problem of spatial estimation of soil CEC with a novel solution, through the combined utilization of statistical, geostatistical and artificial neural network (ANN) techniques. The approach of neural kriging (NK), coupled neural network (NN) with ordinary kriging (OK), has a great potential for predicting and mapping soil properties. The procedure of NK requires information on the coordinates (X, Y) of a survey point in the input. The main advantage of NK approach is its ability in

establishing patterns or nonlinear relationships through training directly on the data without building any complicated mathematical models and making assumptions on spatial variations. It can be seen that this method yields high and significant spatial relations and gives better spatial estimations.

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