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RESEARCH PAPER

A neural network model for estimating soil phosphorus using terrain analysis

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Abstract Artificial neural network (ANN) model was developed and tested for estimating soil phosphorus (P) in Kouhin watershed area (1000 ha), Qazvin province, Iran using terrain analysis. Based on the soil distribution correlation, vegetation growth pattern across the topographically heterogeneous landscape, the topographic and vegetation attributes were used in addition to pedologic information for the development of ANN model in area for estimating of soil phosphorus. Totally, 85 samples were collected and tested for phosphorus contents and corresponding attributes were estimated by the digital elevation model (DEM). In order to develop the pedo-transfer functions, data linearity was checked, correlated and 80% was used for modeling and ANN was tested using 20% of collected data. Results indicate that 68% of the variation in soil phosphorus could be explained by elevation and Band 1 data and significant correlation was observed between input variables and phosphorus contents. There was a significant correlation between soil P and terrain attributes which can be used to derive the pedo-transfer function for soil P estimation to manage nutrient deficiency. Results showed that *P* values can be calculated more accurately with the ANN-based pedo-transfer function with the input topographic variables along with the Band 1.

1. Introduction

Soil phosphorus plays a key role in soil fertility along with other environmental factors; however, long-term soil fertility also depends upon forming practices and fertilizer application. Efforts to predict and assess the spatial distribution of soil P have been done (Wang et al., 2009; Liu et al., 2013; Rubæk et al., 2013; Roger et al., 2014). The estimation of soil

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phosphorus using conventional methods needs extensive labor, is time consuming and also lacks spatial exhaustiveness. Therefore, it is necessary to develop and use alternative and potential methods for soil phosphorous estimation. Modeling of soil-landscape relationships has been used successfully at various scales to estimate soil properties using terrain attribute analysis (Omran, 2012a). Soil phosphorus at landscape level could be better to predict secondary variables using primary variables which are easy to measure and the inverse of these could be correlated with primary variables (McBratney et al., 2003). Applying auxiliary data that have a good correlation with soil properties might be a better option for accurate soil mapping and estimation of physic-chemical properties (Mckenzie and Ryan, 1999; Moran and Bui, 2002). Efficiency of terrain attribute depends on several factors i.e., landform complexity, the strength of the digital elevation model resolution and data quality (Wilson and Gallant, 2000). Appropriate sampling, detailed analysis associated auxiliary variables and application of selected methods prove to be helpful for the estimation of soil properties (McBratney et al., 2003). These methods need a small sample size and therefore, labor, time and are cost effective (McBratney et al., 2003). Various statistical models have been used for the investigation of relationships among spatial distribution of soil attributes and landscape attributes. Predictive mapping techniques i.e., geostatistics, fuzzy logic, linear and multiple regression, regression trees and neural networks have been successfully used for soil mapping (Scull et al., 2005; Arun and Katiyar, 2013).

The ANN is a computational structure, inspired by the study of biological neural processing (Thurston, 2002). A neural network consists of a number of interconnected elements known as neurons and two important elements of neural networks are the types of neural interconnection arrangement and algorithm type used to set the strength of relations. These algorithms are used to model the complex interaction of the environmental systems and interactions without computing the explicit formulation of the relationships that might exist among variables (Omran, 2012b). Neural networks have been successfully applied for the estimation of several difficult-to-measure soil characteristics (Merdun et al., 2006; Landeras et al., 2008). One of the advantages of using ANNs versus conventional models is that it does not require determining a specific function to express the relationship between input and output variables and can be achieved by the train analysis (Schaap and Bouten, 1996).

The ANN method is proffered to estimate difficult-to-measure soil characteristics due to their ease and inexpensiveness. The most commonly investigated model in the soil characteristic estimation is multivariate regression analysis (McBratney et al., 2002). However, the developed model for one region may not provide a good estimation for other areas (Wagner et al., 2001). Therefore, the present work is an attempt to develop a neural network model to estimate its feasibility to measure soil phosphorus from the Kouhin area, Qazvin province, Iran.

2. Materials and methods

2.1. Site description

The hilly area in the northwestern province of Qazvin (Kouhin region), Iran was selected for this study (Fig. 1). Height amplitude varies from 1300 to 1600 m above the sea level with 1–6% slope. This belt covers about 1000 hectares, situated between latitude of 36° 20′ to 36° 23′ north and longitude of 49° 34′ to 49° 38′ east. The climate of the selected area is semi-arid in nature. The soil temperature and moisture regime are mesic and xeric, respectively (Newhall and Berdanier, 1996). Soils have been developed on the surface of alluvial deposits of marl and brown to gray limestone parent materials and are covered by a plateau from the east to west direction. The soil has been classified as Entisols and Inceptisols (Soil Survey Staff, 2013) and is used for rainfed farming. During 1993–2006, the average annual rainfall and average annual temperature were recorded to be 327 mm and 11.2 °C, respectively (Iran Meteorological Organization).

2.2. Field sampling and laboratory analysis

Grid mapping method was used for sampling by dividing the zone to be mapped into small patches of similar size (300 * 300 m). This leads to making observations (profiles or auger) at the nodes of a regular net. Few samples were taken from off-grid to present different physiographic positions. A total of 85 soil samples (20 cm depth) were collected. Geographical location of sampling points was recorded by global positioning system (GPS). The collected soil samples were air dried, crushed and sieved using a 2 mm sieve size and subsequently subjected to analysis. Soil properties such as particle size distribution (Gee and Bauder, 1986), organic carbon (OC) content (Black, 1982), cation exchange capacity (CEC) (Bower et al., 1952) and available phosphorus (Olsen and Khasawneh, 1980) were measured (Table 1).

2.3. Acquisition and derivation of environmental covariates

2.3.1. Topographic attributes

The terrain attributes i.e., slope value, aspect, elevation, hillshade, plan curvature, flow direction and flow accumulation were extracted from a digital elevation model (DEM) with a resolution of 10 m (Fig. 2) (Wilson and Gallant, 2000). After extracting DEM features using geographic coordinate sampling points, the corresponding values of each parameter at each sampling point were extracted and by applying cross operation the numerical values were obtained for selected points (Arun, 2013). The slope (in degree) represents the maximum rate of change of elevation among cell and related parameters.

2.3.2. Vegetation attribute

Geometric corrections of images were performed using digital elevation model and ortho procedures while using landsat-8 satellite image (2013). The satellite images were processed by spectral ratio, principal component analysis and Tasseled Cap transformation. Digital and visual image classifications were conducted in integrated manner and values of Bands 1, 2 and 3 at each sampling point and were extracted using PCI Geomatica software. The NDVI was used to quantify the vegetation at each pixel. The NDVI is a greenness index that is related to the proportion of photosynthetically absorbed radiation and reflects the chlorophyll activity in plants. Within a remote sensing pixel, an increase in NDVI value signifies an increase in green vegetation. Therefore, NDVI was derived

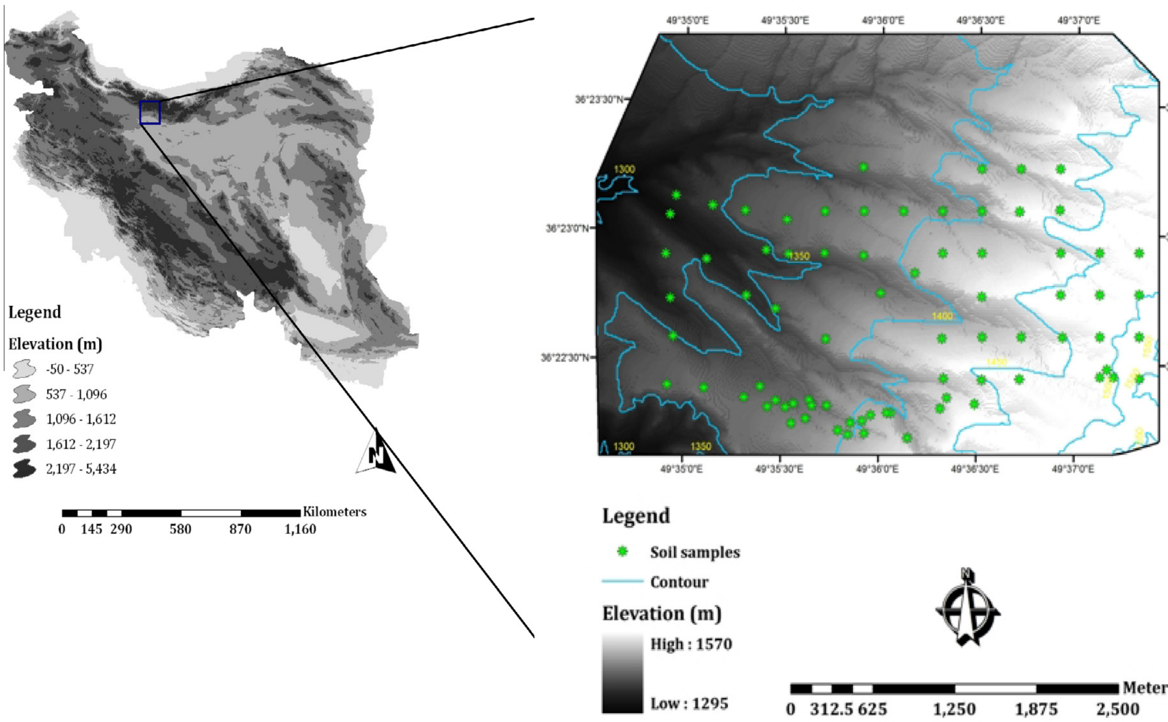

Fig. 1 Location of soil samples in the study area.

Table 1 Data summary statistics of soil and terrain parameters.

Variable	Unit	Mean	Max	Min	Skewness	Kurtosis	C.V. (%)
Available P*	mg/kg	1.01	1.38	0.65	0.30	−1.38	48.32
Clay	%	40.70	59.00	25.00	−0.18	−0.82	22.59
Silt	%	26.30	44.00	16.00	0.60	0.66	21.70
Sand	%	32.00	57.00	10.00	0.43	0.33	34.95
OC	%	0.68	1.33	0.13	0.39	−0.69	42.64
Slope**	%	3.07	5.80	0.91	0.45	1.05	52.93
CEC	$Cmol^{+}\ kg^{-1}$	23.08	29.43	17.03	0.13	−0.38	12.35
Elevation	Meter	1404.50	1543.33	1311.40	0.69	0.32	3.80
Plan curvature	Deg/m	−0.01	0.26	−0.21	0.59	2.36	63.16
Band 1	–	122.77	151.00	77.00	−0.44	−0.68	16.23
Band 2	–	99.02	142.00	54.00	−0.58	−0.66	22.71
Band 3	–	109.34	144.00	65.00	0.59	−0.87	20.96
NDVI	–	0.11	0.28	0.02	0.69	0.85	33.90

* Logarithm transformation.
** Square root transformation.

using Landsat-8 on February 2013 at a spatial resolution of 30 m × 30 m.

Values of NDVI range from −1 to +1 with vegetated areas typically having values greater than zero being considered. The NDVI can be considered as an indirect indicator of the amount of biomass added to the soil, which may be related to the OC soil content. Changes in NDVI also correspond to changes in the vegetation health, thus intimating at the availability of water to the plant and in turn to the the bulk density, pore size/structure evolution and the soil hydraulic properties.

2.4. Data pre-processing and development of pedo-transfer functions

Statistica (version 10.0) and SigmaPlot (version 12.0) statistical software were used for data processing. Before selection of input (independent) and output (dependent) variables, data points were tested through the Kolmogorov–Smirnov test (Mohammadi, 2002). Outliers were separated and data normality was confirmed. For non-normal data, required transformation (logarithm, square root) was used. The correlation between variables was examined through forward stepwise regression analysis and most influential parameters were selected (Dashtaki and Homaei, 2002). As a result, elevation, slope and Band 1 were used as the input values for the ANN and soil phosphorus values and were applied as the output in the development of pedo-transfer function (Table 2).

Data points were standardized for equalization before the ANN model training, which prevents excessive shrinking weights. The data points were converted between 0 and 1 numbers since most of the output threshold functions were found

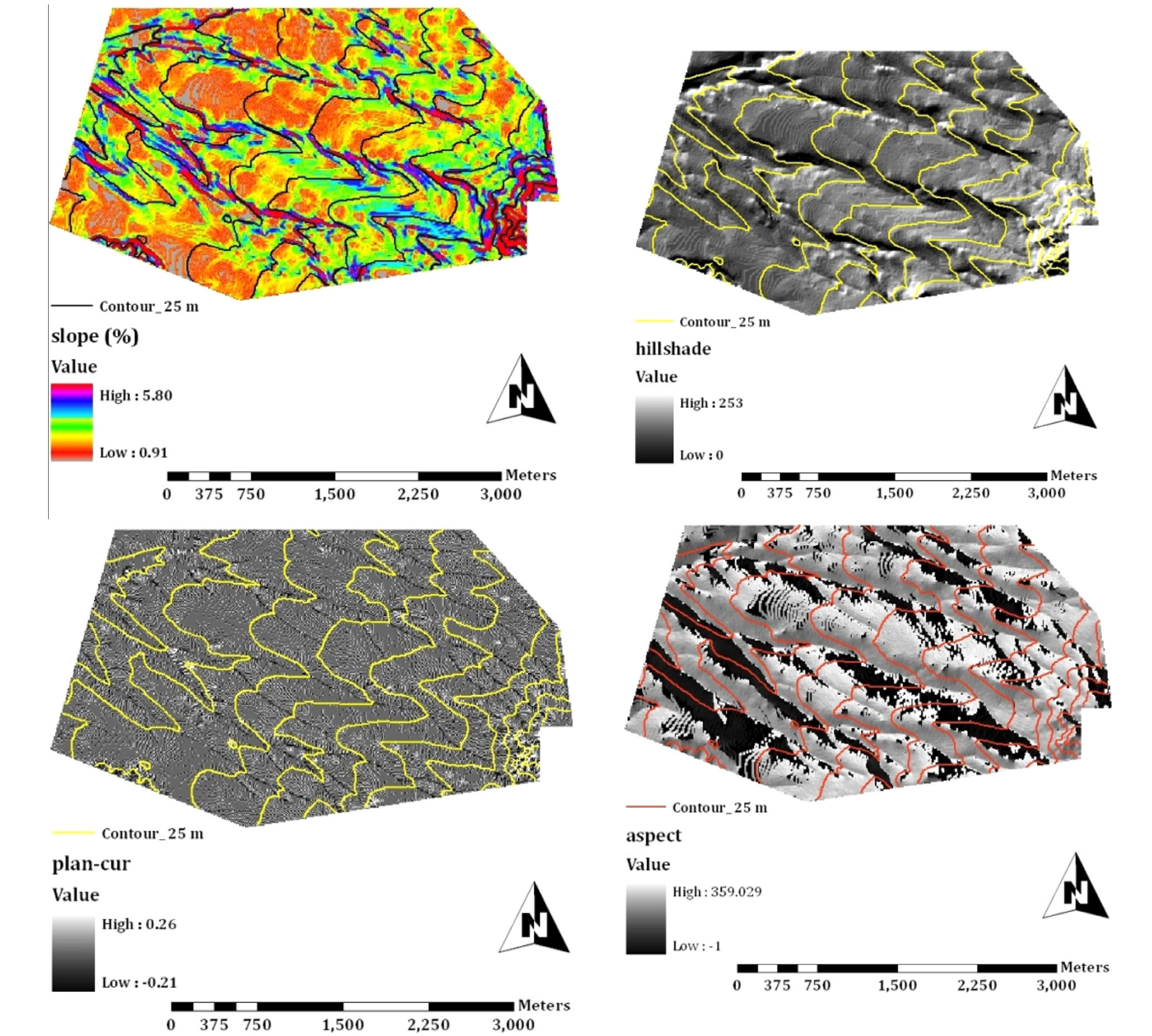

Fig. 2 Some environmental covariates.

within this range. For the conversion of data, the data points were normalized using the relationship (Eq. (1)):

$$y_{\text{normal}} = (y_o - \bar{y}_i)/(y_{\max} - y_{\min}) \tag{1}$$

where, $y_{\max}$ is the maximum data, $y_{\min}$ is the minimum data, $\bar{y}_i$ is the mean value of measured values, and y_o presents observed values.

2.5. *Artificial neural networks*

Information from the elevation, slope, flow accumulation, and NDVI grids was interpolated and combined with soil information collected from the soil analysis. Different models using different combinations of soil-topography-vegetation attributes as input were developed to predict soil phosphorus. Neural classifiers deal with numerous multivariable nonlinear problems, which is an accurate analytical solution, but difficult to obtain (Park et al., 2010). The structure of a feed-forward ANN is shown in Fig. 3. This ANN is a popular neural network which is known as the back propagation algorithm (Karaca and Ozkaya, 2006). This ANN had k input and one output parameter. They used this ANN for accurate modeling of the flow rate and it is reported that the input parameters,

Table 2 Pearson correlation coefficients (r) between selected variables in the study area.

Variable	Available P (mg/kg)	Elevation (m)	Slope (%)	Band 1
Available P (mg/kg)	1	0.673**	0.512**	0.559**
Elevation (m)		1	0.193	0.285
Slope (%)			1	−0.08
Band 1				1

** Significant at 0.01 level.

number of neurons at the hidden and output layer can be determined from collected 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 mechanisms (Pachepsky et al., 1996; Schaap et al., 1998). In the feed-forward networks, error is minimized by different procedures namely gradient descent (GD), Levenberg–Marquardt (LM) and Conjugate Gradient (CG). Back propagation (BP) uses a gradient descent (GD) technique, which is very stable when a small learning rate is used, but has slow convergence properties (Farjam et al., 2014). The term ''Back propagation'' refers to the way the error is computed at the output layer of the ANN, which is propagated into the hidden layer where all computations are made. 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.

2.6. Performance criteria

The model performance was evaluated using test data points that were not used in the network training. The parameters used for the evaluation of model were root mean square error (RMSE) and coefficient of determination (R^2), (Wosten et al., 2001). MATLAB software (version 7.10) was used for designing and testing of the ANN model. The neural network structure has no high extrapolation strength and its generalization capability is considered only in the context of interpolation. The training data was selected as a representative that maintains all possible (maximum and minimum) values. Therefore, the data points were divided by the randomization technique. Data points were randomized by Excel software (window 7) (Amini et al., 2005) and 80% of the data was selected to train the model and remaining 20% was used to test the developed model. Selected topographic indicators (terrain attributes) and remotely sensed data were input for prediction of the output (Soil P). During the learning process of the ANN model, learning rate was measured by the network using objective functions. Finally network with the lowest error rate was selected (McBratney et al., 2002). For this purpose, Levenberg–Marquardt training algorithm was used because of its efficiency and simplicity. In this study, the ANN structures consisted of one hidden layer, a sigmoid activation function in the hidden layer and a linear activation function in the output layer and the LM algorithm was used to train the network developed. To develop a statistically significant model, the developed network was trained 3 times and the best values were recorded for each parameter. To avoid ''over-fitting'', the RMSE of the CV subset was calculated after adjustment of weights and biases of data. Then the network adapted weight and bias were employed for validation of the model in order to determine the model's overall performance.

3. Results and discussion

3.1. Data processing and analysis

After data processing and outlier elimination, the data number reduced to 77 points, which were processed further using the ANN model. Table 1 shows the statistical summary of the soil properties used for training and testing of the model. Soil phosphorus minimum, maximum, mean, standard deviation (SD), skewness and kurtosis are shown in Table 1. Since skewness was less than 1, so, data were not transformed further. Relatively wide range of variations was observed in soil properties. Variation of 25–59% was recorded in clay particles, whereas OC content varied from 0.13% to 1.33% with an average value of 0.68. The CV of soil OC was found to be high, which might be due to the application of fertilizers and resultantly, the soil OC improved. Fard and Harchagani (2009) also reported a high coefficient variation of soil OC and correlated it with fertilizer application. The observed difference in soil properties could influence the phosphorus content because its sorption and desorption may change under a certain set of environmental conditions (Stutter, 2015).

High coefficient of variation indicates high spatial variability of parameters studied. Coefficient of variation for soil OC, available phosphorus and slope was high, which reveals high variability in this specification. On the other hand, elevation and Band 1 parameter coefficient of variation was low. The difference between coefficient of variation in the terrain feature and soil parameters in the study area is attributed to sampling geometry, physiographic of plateau and slope variations (Roger et al., 2014).

The effect of topography on the distribution of soil particles, OC and nutrients is influenced by erosion and deposition. Table 2 shows Pearson correlation coefficient (r) between selected variables (terrain attribute and soil P) in the study area. The results show that the available soil phosphorus with topographic features derived from digital elevation model have a good correlation with height ($r = 0.673^{**}$), slope ($r = 0.512^{**}$) and Band 1 ($r = 0.559^{**}$). Although these correlations are significant, however, due to the variation in topography they are not as strong as which could be.

3.2. ANN model for soil P estimation based on terrain attributes

In the present investigation, the most influential parameters were selected through forward stepwise regression analysis. The input variables (slope, elevation and Band 1) were used to develop the ANN model and resultantly, a significant correlation was observed among the input variable and soil phosphorus. The model was developed, primarily trained with training data sets and used for the prediction of error rate against a number of hidden layer neurons. Trial and error method was used in order to find out the optimal number of hidden neurons. Fig. 4 shows the 3D surface plot of soil phosphorus versus elevation and Band 1 data. Based on the plot of input variables and spline function for the prediction of soil phosphorus the input data for constructing ANN did not increase.

Increasing the number of input variables may decrease the accuracy of the estimates because only one parameter may influence the output due to low value of correlation coefficient determination and resultantly, the accuracy of the model may decrease (Amini et al., 2005). After randomizing and splitting of data set into training and testing data, various ANN structures of topology 3-k-1, i.e., network was designed. The optimum structures of network were estimated from R^2 and RMSE values and results, thus obtained are shown in Table 3.

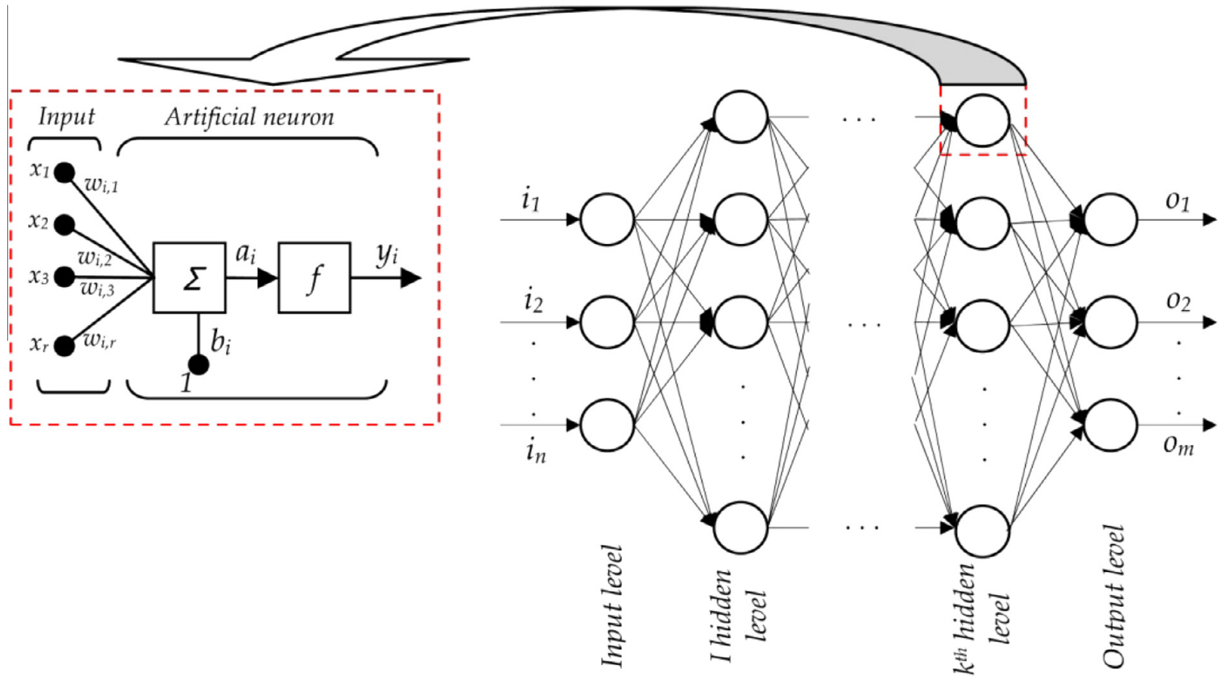

Fig. 3 Structure of feed-forward ANN (Tanikic and Despotovic, 2012).

3.3. Sensitivity analysis

To determine the effect of each input parameter on the soil phosphorus, sensitivity analysis is reliable and performed to check the sensitivity. Sensitivity analysis of input parameters of the network was performed using Statistica statistical software (version 7.0, 2004) and input parameters showed considerable effect on the output. The results of sensitivity analysis of the selected input are shown in Fig. 5.

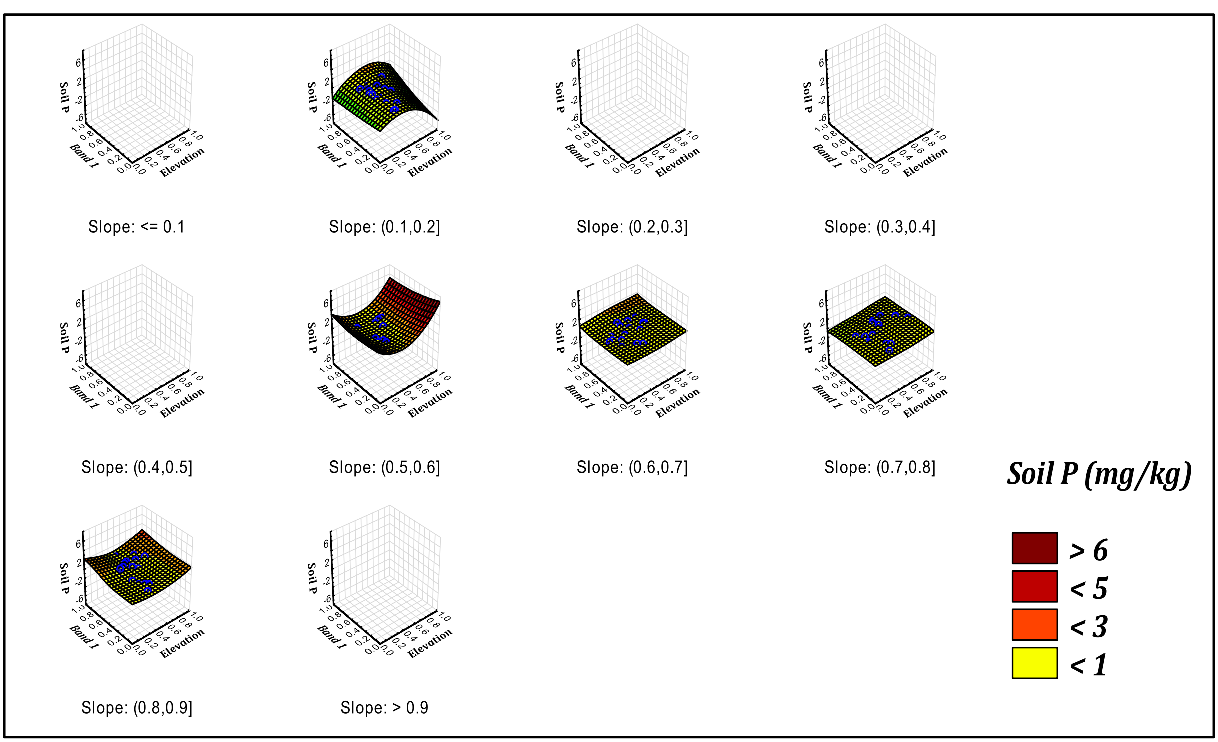

Fig. 4 3D surface plot of soil P vs. elevation and Band 1; categorized by slope gradient using spline function.

Table 3 The best performance of ANN model for estimating soil P.

Parameter	Topology	Training algorithm	Activation function	Epoch	RMSE (%)	R^2
Soil P	3-6-1	LM*	Sigmoid	752	1.65	0.68

* LM = Levenberg–Marquardt.

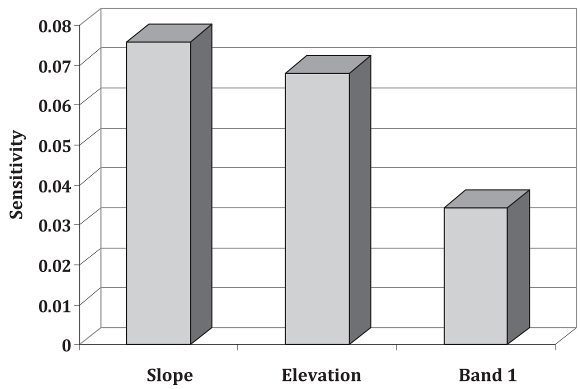

Fig. 5 The result of sensitivity analysis on input parameters.

As it is clear from data, the neural network model indicated highest sensitivity to slope and elevation, respectively. Hence, it indicates the strong influence of slope on soil phosphorus variation. As can be seen from Table 1, the high coefficient of variation was obtained, which indicates high spatial variability of the study features. Thus, high coefficient of variation of slope (52%) showed better sensitivity of the data analysis.

3.4. Model performance evaluation

In order to assess the ANN model performance, test data points were used to predict soil phosphorus and predicted values were plotted against observed values. Fig. 6 shows the scatter plot of the observed versus predicted values for the soil phosphorus model. The plot approximates a straight line, and an angle close to 45° (one to one line), which indicates the high accuracy of the ANN model for the estimation of soil phosphorus. The application of ANN model in predicting soil phosphorus explained 68% variation. Previously, similar studies conducted by Pilevar Shahri et al. (2011) and Lakzian et al. (2013) also indicated the neural network model could justify 80% and 56% of soil OC, respectively, using digital elevation model derived parameters.

4. Discussions

It is difficult to approximate with state-of-the-art soil-landscape modeling assessments of environmental layers. The moderate relationship between soil phosphorus and selected predictors (variables) in the present investigation ($R^2 = 0.68$) highlighted some important issues and are discussed. It is well known that in calcareous soils of Iran that are evolved in arid and semi-arid regions, a larger part of soil phosphorus is retained by the reactions of absorption and illuviation of carbonate minerals (Musavi and Sepehr, 2013). Chemistry of phosphorus in soils is very complicated because inorganic phosphorus reacts with calcium, iron and aluminum and is converted into phosphates. Additionally, organic phosphorus can be found with a variety of shapes and resistance to microbial degradation in soil (Soltani et al., 2011). Therefore, the variation in the amount of OM and the lime in the study area can make a difference in the amount of available phosphorus in soils and consequently, the variation coefficient may increase.

The NDVI information helped to improve model precision. Land use practices have a major impact on soil OC content. Results presented could be interpreted that the impact of current land use on the distribution of soil OC and soil phosphorus are relatively small versus topographic impacts. Furthermore, land use itself is determined by the topographic conditions and some of the land use impacts had already been represented in the topographic derived parameters (Zhao et al., 2010). Land use may affect the relationship among variables and previously similar findings have been reported (Jia et al., 2011; Lemercier et al., 2008; Reijneveld et al., 2010). Moreover, the use of auxiliary data such as DEM as well as sub-division of the study area may improve the prediction by

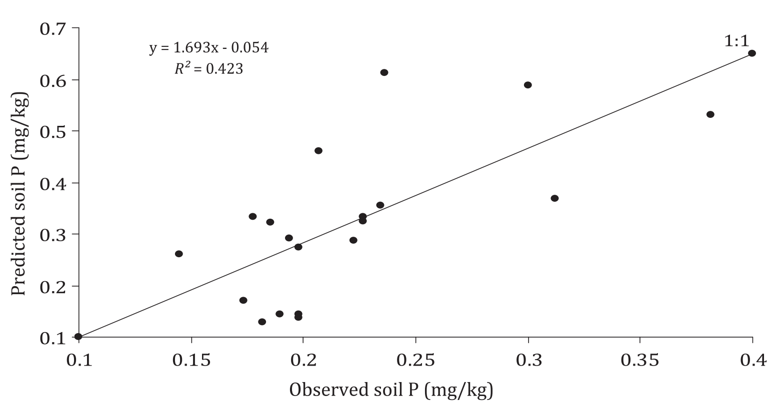

Fig. 6 The scatter plot of the observed versus predicted values for soil P model (Data were normalized between 0 and 1).

reducing the overall variability and soil phosphorus relationship with environmental factors could be deduced precisely. For this, a valuable and inexpensive source of secondary information (DEM) is required, which provides explanatory variables for predicting and developing a model for soil phosphorus estimation. Topography influences soil properties due to local re-distribution of water, solar radiation and material, etc. (Gessler et al., 2000; Kozar et al., 2002).

The technical sources of uncertainties, as for instance the accuracy of the DEM and the localization of sampling sites with the global positioning system (GPS), also limit the model performance. Lakzian et al. (2013) highlighted that estimation of soil OC using the neural network model is most sensitive to the wetness index. Moreover, slope and elevation were the next priorities in sensitivity analysis. Elevation showed the least sensitivity among input parameters. The results of sensitivity analysis conducted by Pilevar Shahri et al. (2011), showed the highest sensitivity to network profile curvature parameters. Due to non-linear relationship between dependent and predicted variable (P), ANN model showed good performance. Therefore, using different trained models and test data sets, the accuracy of the ANN model in predicting phosphorus can be improved.

5. Conclusions

The neural network model was developed and its feasibility for soil phosphorus estimation was checked from rainfed areas using terrain attributes including elevation, slope, and Band 1 data based on RMSE and R^2 values. The results indicate good accuracy of the model and a 68% variation in data was justified. The correlation among input and output variables from terrain attribute analysis confirms the applicability of the model in predicting soil phosphorus contents. The ANN model can be soil phosphorus content determination using soil topographic attributes. Furthermore, to avoid the uncertainties in data due to natural phenomena associated with different soil properties and uncertainties in the data, hybrid models such as neuro-fuzzy, which use fuzzy sets, could possibly be used in processing and fitting the pedo-transfer functions with more reliability.

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