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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