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PREDICTION OF SOIL TEXTURE USING FEED FORWARD NEURAL NETWORKS

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Abstract-The contribution deals with prediction of soil texture using an artificial neural network approach namely Feed Forward Neural Network (FFNN) model. Subsequently we are comparing this approach with Self Organizing Map (SOM) using data from the remote sensing department, Agriculture University Coimbatore, India. The proposed Feed Forward Neural Network model predict soil texture like sandy loam, clay and silt based on soil attributes which has been collected from the field observation. To achieve this soil samples were taken from 50 points. Soil samples were analyzed for the percentage of sand, silt and clay. The data which was collected from field observations were used to construct the neural network model. An experimental result shows that the performance of FFNN performs well than SOM.

Keywords Artificial Neural Network, Soil attribute, Remote sensing.

I. Introduction

Soil texture is an important characteristic of soils, greatly influencing fertility, water-holding capacity, and productivity. Accurate soil texture information is important to farmers to take decisions regarding profit and environmental stewardship. Doing so requires an understanding of the functional relationships between soil, other site properties, and feasible field activities Drummond et al.,[1998].

Neural networks or simply neural nets are computing systems, which can be trained to learn a complex relationship between two or many variables or data sets. Having the structures similar to their biological counterparts, neural networks are representational and computational models processing information in a parallel distributed fashion, composed of interconnecting simple processing nodes [P.De. Wilde ,1997]. Neural networks build a mathematical model that works like a human brain. Neural networks can perform a function when certain values are assigned to the connections or 'weights' between elements. To describe a system, there is no assumed structure of the model, instead the networks is adjusted or 'trained' so that a particular input leads to a specific target output [Gershenfeld, 1999]. This model comprises of a set of functions linked together with weights. The network consists of input units, output units, and hidden units. Neural networks are now widely used in the soil science literature, mainly for predicting soil attributes. The application of neural networks as pedo transfer functions for predicting soil hydraulic properties is the most common [McBratney et al, 2003]. To know the suitability of a soil for any particular purpose first it should be categories based on any one of the classification systems. The classification of a soil needs more information about its chemical and physical properties that require laboratory analysis to determine their values. Organic matter, texture can be determined from color and hand Texturing. All over the world the scientist is investigating the possibility of introducing information technology and science to soil survey. The principal manifestation is soil resource assessment using geographic information systems (GIS) [McBratney et al, 2003].

II. Related Works

Nowadays numerous researchers are investigating the possibility to apply new tools and techniques to soil science.It helps to understand the soil properties .Zhu[2000]redicts the soil classes from environmental details.Fidencioet al.[2001]sed radial basis function and SOM to classify soil in the region of saopaulo.Mcbratney[2003] gave a detailed survey on digital soil mapping based on geographic information system.Voltz et al[1990]predicted the percentage of clay in soil using krining method and cubic spine method.Oberthur et al.[1996] classified the soil using field texturing and particle size.Ramadam et al.[2005] gave PCA and back propagation ANN to predict soil properties like sand,siltetc.,Zhengyong[2009]developed on Neural Network model to predict soil texture based on soil attributes from coarse resolution soil maps which was combined with hydrographic parameters taken from a digital elevation model.Marcant et al.[2003]used compared Bayesian classifier with feed forward neural network using plant, Soil discrimination in colourimages.Sofianita[2010]classified the soil by its characteristics like colour ,texture, terrain and drainage.Venkatesh et al[] predicted the plant growth by multilayer perception neural networks.

III. Materials And Methods

A. Study site

This zone comprises of 7 districts viz., Coimbatore, Erode, Namakkal, Karur, Dindigul, Madurai and Theni. The zone has undulating topography sloping towards west to east with small hillocks here and there having an altitude

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ranging from 171 to 1525 m above MSL. The western and northern parts of the

zone are bounded by the Western Ghats bordering Kerala and Karnataka states with peaks ranging from 1000 to 2700 m above MSL. The Nilgiris on the North-west and Anamalais on the South are the chief ranges that attain heights over 2400 m. The eastern part of the zone is bordered by the Namakkal ,Karur and Dindugul Districts. The southern part of the zone lies in Madurai and Theni districts having contours of various altitudes. The northern part of the zone bordering Karnataka state which contains one block namely Thalavadi, has undulating plains and hills. The rest of the area is an undulating plain sloping gradually from west to east.

B. Soil Sample Collection and Measurements

The soil of modakurichi was surveyed at a scale of 1:10,000.Soil profiles (75 points) were surveyed for every 5 ha of agricultural land ,the soil data like sand% and clay % were analyzed and based on this the soil texture was identified, Apart from this soil PH was also identified using laboratory analysis .The soil layers and soil depths were also considered in our study area. The soil of modakurichi was surveyed and classified into different groups. The texture varied from sand to clay.

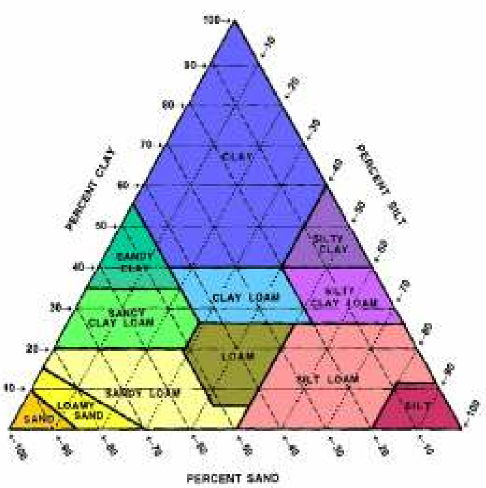

Figure 1

The soil is made up of small particles . Soil particles vary in size, shape and chemical properties. There are three types of soil particles like sand, silt and clay. These groups are called soil separates. The proportion of soil separates in a soil gives the soil texture. Totally there are 12 classes of soil texture. A textural triangle can be used to determine soil textural class. It represents all possible combinations of soil separates. According to the soil texture triangle. A sandy loam has 60% sand, 10% clay and 30% silt. Texture means the size of the particles that make up the soil. Sand, silt, and clay refer to the sizes of the soil particles. Sand particles are larger in size. Silt is moderate in size and has a smooth texture. Clay particles are smaller in size. D stands for depth, L stands for layer.

Table 1: Sample Data

SOIL_CODE	LD	SD	MIN_D	MAX_D	SAND_PER	SILT_PER	CLAY_PER	TEXTURE
100206090807090222	2	16.0	35.0	51.0	40.5	26.7	32.8	Clay loam
100206090807090222	3	51.0	51.0	102.0	43.0	11.0	46.0	Clay
100206090807090222	4	50.0	102.0	152.0	40.0	17.0	40.0	Clay loam
100206091207090034	1	11.0	0.0	11.0	52.0	22.0	26.0	Sandy clay loam
100206091207090034	2	37.0	11.0	48.0	45.0	19.0	36.0	Sandy clay
100206091207090034	3	60.0	48.0	108.0	46.0	20.0	38.0	Sandy clay
100307000807090237	1	34.0	0.0	34.0	46.3	24.7	42.0	Sandy clay
100307000807090237	2	61.0	34.0	95.0	75.8	44.8	19.4	Sandy loam
100307000807090237	3	60.0	95.0	155.0	24.0	57.0	24.1	Silt loam
100405031207090209	1	10.0	0.0	10.0	47.40	39.5	23.76	Loam
100405031207090209	2	58.0	10.0	68.0	70.38	21.02	48.6	Sandy clay
100405031207090209	3	32.0	68.0	100.0	43.88	42.14	49.98	Clay
100405031207090209	4	45.0	100.0	145.0	40.11	23.41	47.48	Clay
100406030807090165	1	16.0	0.0	16.0	78.15	9.48	12.37	Sandy loam
100406030807090165	2	45.0	16.0	61.0	18.6	51.85	46.55	Siltyclay
100406030807090165	3	41.0	61.0	102.0	63.15	8.0	28.85	Sandy clay loam
100406030807090165	4	33.0	102.0	135.0	55.45	7.65	36.9	Sandy clay
100406080307090416	1	10.0	0.0	10.0	79.14	23.25	17.61	Sandy loam
10040608030709	2	62.00	10.0	72.0	73.0	3.42	23.58	Sandy clay

0416								loam

IV. Neural Network Architecture and Training

In this approach, the new feed forward neural network is proposed to find a solution to the soil texture classification problem

A. Structure of the FFNN

The architecture consists of n input units, one hidden layer with n sigmodial units and a linear output. Each neuron produces its output by computing the inner product of its input

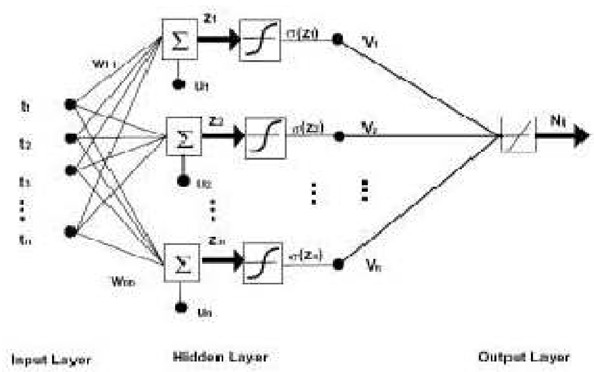

Figure 2.Neural Network Architecture.

While training, the weights and biases of the network are iteratively adjusted by Nguyen and Widrow rule [33].The neural network architecture is given in the Fig. 1 inComputingN_{ij}. The neural network algorithm was implemented in MATLAB on a PC, CPU 1.7 GHz for the neuro computing approach.

Neural network algorithm

Step 1. Feed the input vector t_j.

Step 2. Initialize randomized weight matrix W_{ij} and bias u_i.

Step 3. Compute $Z_i=\sum_{j=1}^{n} W_{ij} t_j + u_i$

Step 4. Pass z_i into n sigmoidal functions.

Step 5. Initialize the weight vector v_i from the hidden unit to output unit.

Step 6. Calculate $N_{ij} = \sum_{i=1}^{n} \vartheta_i \sigma(z_i)$

Step 7. Compute Purelin function (N_{ij}).

Step 8. Repeat the neural network training until the followingerror function$E = \sum_{i,j}^{n} ((\dot{\vartheta}_i \dot{I}_j)_2 - \emptyset_{ij}(t,(\dot{\vartheta}_i \dot{I}_j)_a))^2 = 0$

V. A Self-Organizing Map (SOM)

A self-organizing map (SOM) is a type of artificial neural network (ANN) .Self-organizing maps is different from other artificial neural networks algorithm .SOMs is useful for visualizing low-dimensional views of high-dimensional data, similar to multidimensional scaling. The artificial neural network is also known as Kohonen map or network.[1][2] which is very helpful in building biological models of neural systems. SOMs operate in two modes like training and mapping, Training builds the map by using examples which we are giving as an input and the other mode mapping repeatedly classifies a new input vector.In SOM there is no need of target output to be specified like that of other types of network. Node weights should match the input vector as an alternate. Each zone is a efficient feature classifier and previously hidden input vectors presented to the network will kindle nodes in the zone with similar weight vectors.

Training occurs as follows with much iteration:

(i) Node weights of each node is initialized.

(ii) Randomly a vector is chosen from the training data set and presented to the network.

(iii) Node are examined to analyze one's weights that is moresimilar like the input vector and is known as the Best Matching Unit.

(iv)The radius of the neighborhood of the BMU is now calculated and nodes found within this radius are considered to be inside the BMU's neighbourhood.

(v) Neighbouring node's weights of each node is adjusted and altered.

(vi) Repeat step (ii) for N iterations.

VI. Results

The analysis and interpretation of predicting results requires a profound understanding of statistics and it requires more time. The research activities helps in predicting accurate results by using feed forward neural networks with the available dataset. The aim of the research was to determine how well soil texture can be predicted by using FFNN and SOM and to find out which algorithm can well in the available data set.The samples used in this study were limited, 17 sampling locations (60 soil samples) per farm. Satisfactory predictions were possible for clay, sand, loam etc. Prediction errors of around 4% for clay and silt, 3–6% for sand if we go for Feed Forward Neural Network(FFNN) and Prediction errors of around 6% for clay and silt, 7–10% for sand was the prediction result of Self Organizing Map (SOM)

VII. Conclusion

The proposed work represents prediction of soil texture using feed forward neural networks improved performance and accuracy. In this we have also done analysis by applying two methods, one is the feed forward neural network approach and second one is self organizing map both results are compared and feed forward neural networks algorithm produces better results than that of the self organizing map approach .

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