

An intelligent System for Soil Classification using Supervised Learning Approach

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Abstract
Agriculturist or farmers collect soil sample that are later analyzed for proper classification. This conventional procedure is labour intensive, time consuming and expensive. In this research work, an attempt was made to develop an intelligent system that can identify different types of soil in a particular location using the available hyperspectral data at such location with supervised learning approach. The system was developed using fuzzy – C means to identify the cluster centre. The cluster center was used as an input to train KSOM and generate soil prediction map as an output. ANFIS was eventually used to identify each class of the soil using the soil predictor map as an output during the training stage. The system was implemented using R programming Language.
Keywords: Hyperspectral data, C-Means Clustering, KSOM, ANFIS, Supervised Learning, Intelligent System,

1. Introduction

The idea of developing an intelligent system emanated from a particular branch of computer science called artificial intelligence (AI). AI may be defined as a branch of computer science that is concerned with automation of intelligent behaviour [22].

However, this definition suffers from the intelligent itself i.e. it is not well defined or understood. Intelligent is a capacity of a system to achieve a good or sustain desired behaviour under conditions of uncertainty.

Intelligent system has to cope with sources of uncertainty like occurrence of unexpected event such as unpredictable changes in the world which generate an incomplete, inconsistent and unreliable information to be made available to the system for the purpose of deciding what to do next. Intelligent system therefore exhibits the following behaviour.

According to Nicola [15], an intelligent system exhibits the following behaviour:

(i) They should from time to time accommodate new problem solving rule
(ii) They should be able to analyze themselves in term of behaviour error and success.
(iii) Once they are to interact, they should learn and improve through interaction with environment
(iv) They should learn quickly from large amount of data
(v) They should have memory based examples, storage and retrieval capability
(vi) They should have parameter to present

Agris [1] also summarized basic features of intelligent system as follows:

(i) They have the ability to generate a new knowledge from already existing ones
(ii) They have ability to learn
(iii) They have ability to sense environment
(iv) They have ability to act

A lot of research work has been done in the area which involves development of an intelligent system to solve various real life problems.

However, literature reveals that enough has been done in the area of Agriculture most especially in the aspect of soil classification or identification. Therefore, this research work made an attempt to develop an intelligent system for soil classification using supervised learning approach.

2. Statement of the Problem

Traditionally, the spatial variability of soil property is obtained via field grid sampling [2]. Farmers or Agriculturist collect sample that are later analyzed for proper classification/ identification. This conventional procedure is labour intensive, time consuming and expensive.

This calls for a better approach. This research work therefore is to develop an intelligent system for soil classification making use of supervised learning approach. It will serve as a useful tool in the area of Agriculture, land use and soil management.

3. Significant of the Study

Soil plays a fundamental role in sustainable land use by supporting valuable services as biodiversity, food production and pollution buffering [18]. Vital human and plant activities depend on this important non-renewable resource.

In fact, it is a gift of nature which sustains the life of all living creature. Without soil, there will be no life. One of the major components of soil is minerals which are highly needed by plants and animals for their continuous existence.

This research work will provide adequate information on soil properties (Classification). Lack of such information could lead to uncertainty in the prediction of food production, rock formation, mineral production and some other basic amenities. Non-availability of such information will also lead to poor management of this natural gift. Again, despite various types of soil surveying being carried out in different countries, the scale and spatial covering of many conventional soil maps are not sufficient enough for planning and maintaining soil facilities at national and international level.

This research will provide an automated information which will be better than the initial ones

4. Objectives of the Study

The objectives of this research are:

(i) To develop an intelligent system for soil classification
(ii) To develop such intelligent system using supervised learning approach.
(iii) To implement the system with hyperspectral data using R programming Language.

5. Literature Review

A lot of research works or investigations have been carried out on soil classification or identification making use of multispectral data.

According to Baojuan [2], as far back as 1960 to early 1970, scientist began to investigate the possibility of using multispectral remote sensing data for differentiating surface soil. With the launching of LandSat satellite in 1972, the research became more broad and meaningful. This is due to the availability of millions of multispectral satellite images for soil survey and mapping. Chen, Dematte and Ray [4][6][17] used multispectral remote sensing to estimate soil property though an intelligent system was not developed.

Early 1980, there was availability of hyperspectral data image since multispectral data cannot produce enough information compared to hyperspectral data. Dalal et al, Marra et al, Masserschmidst et al, Chang et al, Udelhoven et al, and He et al [3] [5] [7] [12] [14] [21] were able to use various methods to predict soil properties but an intelligent system with supervised learning approach that make use of hyperspectral data has not been developed.

Also, Baojuan [2] published an M.Sc. research thesis titled using satellite hyperspectral imagery to map soil organic matter, total nitrogen and total phosphorus. The research was able to test the capability of partial least square regression for mapping soil organic matter and was able to generate soil organic matter in Indiana watershed.

Zhengyong[23] developed a system to predict soil texture using artificial neural network model. He did not use hyperspectral data but multispectral data. The calibrated ANN then could not be used in further predictions of similar conditions without additional field survey. This reduces the intelligent level of the system coupled with the fact that the method used is of less precision. Sergio [18] also developed an ANN system for digital soil mapping.

Stephan [20] worked on hyperspectral analysis of soil Nitrogen, Carbonate and organic matter using regression tree.

Pao-Tsung [16] worked on the classification of organic soils. The research work carried out an in-depth characterization study using a variety of techniques, of a number of organic soil sampled throughout the state of Indiana.

Conclusively, literature reveals that most of the past authors did not actually developed intelligent system that made use of supervised learning and implement such with R programming language using hyperspectral data. This has limited the level of performance of their system.

6. Artificial Intelligence (AI) Methods

There are different methods of AI, this includes:

Neural Network
Fuzzy Logic
Neuro-fuzzy
Genetic Algorithm

6.1 Neural Network

As explained in fig1, the concept of Neural network is born out of biological neural network. It is just an emulation of biological network. The neural network consists of input, processing and output structure. The data in form of an array is fed to the system as the input. A target is set at the output. An error is compared as the difference between the desired response and the real system output.

The error information is fed back to the system through back propagation which makes all possible adjustment to record close to zero error. The process continues until the desired output is acceptable. This is described as learning rule in the network.

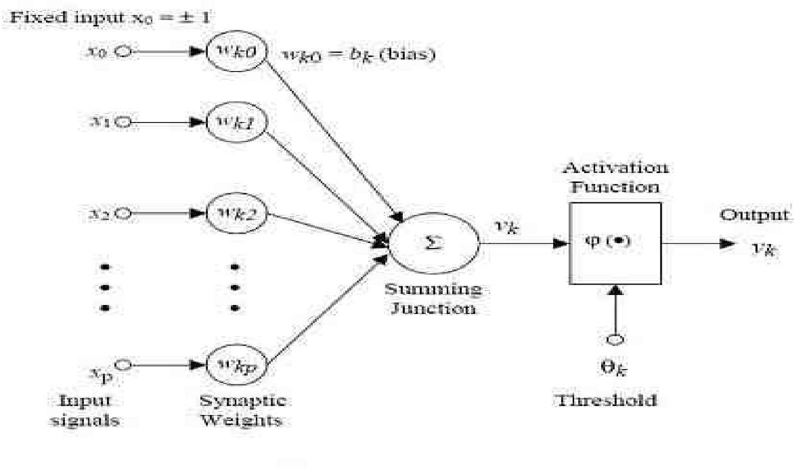


Fig 1: Structure of Neural Network

The outcome of some activation function on the value of vk would be the output of the neuron, yk,

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \qquad \text{……………… (1)}$$

Neural network can perform a non-linear program task. It has a parallel nature and a failure of an element will not affect others. Because of its learning habits, it needs not to be reprogrammed for subsequent operation. It can be implemented to solve problems in different areas of life

6.2 Fuzzy Logic

Fuzzy logic was initiated in 1965 by L. A. Zadeh, professor of fuzzy sets and information, Computer Science Department at university of California in Berkeley. It could be described as multivalued logic that allows intermediate values to be defined between conventional evaluations like True/False, Yes/No, High/Low e.t.c. [8]

Fuzzy modeling use as input features for classification or measures of the process. It is a tool that allows an approximation of non-linear system to be modeled [19].

The fuzzy logic model has several advantages when compared to other non linear modeling techniques. In general, fuzzy model can provide a more transparent model and can also give linguistic interpretation in form of rules. Fuzzy models use rules and logical connectives to establish relations between the variable defined to derive the model [13].

6.3 Genetic Algorithm

In a situation where we have different condition for a task and there is a need to pick the best, genetic algorithm (GA) has been found to be very effective. It makes use of the **evolutionary** nature of our genes. In order to grade the candidate there is emphasis on relationship among criteria and such relationship is expressed in term of fitness function.

To find the best out of possible events, it makes use of evolutionary method such as crossover and mutation on chromosomes. It could also use strands of information. GA use a method called abductive reasoning. This method bails down to sophisticated trial and error [21]. According to Koza et al [11], GA algorithm works as follows:

1. Evaluate the population against “high fitners criteria”
2. If a candidate meets the criteria step 1 else
3. Select the best of the current set using a selection strategy and diversity maintenance, then
4. Reproduce using crossover and mutation, and return to 1

This is a search algorithm. It has been used in different research area to search for elements or minerals in a particular location. Data are not trained for further discovery.

6.4 Expert system

Experts can combine their knowledge to develop a particular system to solve a particular problem using expert knowledge or technique. Such system is referred to as expert system. It is built using large number of rules. A specialist called knowledge engineer extracts the rules from the expert and program them into a computer. Example of such rules includes:

If the body temperature is not greater than 37^{o}C

THEN the patient is normal.

IF the blood pressure is 110

THEN the patient is normal
There is a need to develop an expert system under certain condition:
(i) When there are few experts in a field
(ii) When it is necessary for the system to run without human intervention

6.5 ANFIS (Adaptive Neuro-fuzzy inference system)

Adaptive Neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and approximate membership functions from the stipulated input-output data pairs for neural network training. This procedure of developing a FIS using the framework of adaptive neural networks is called an Adaptive Neuro Fuzzy Inference System (ANFIS). There are two methods that ANFIS learning employs for updating membership function parameters:

1) Back propagation for all parameters (a steepest descent method), and
2) A hybrid method consisting of back propagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output membership functions.

As a result, the training error decreases, at least locally, throughout the learning process. Therefore, the more the initial membership functions resemble the optimal ones, the easier it will be for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting up these initial membership function parameters in the FIS structure [9][10]. The general ANFIS architecture is shown in Fig 2 below

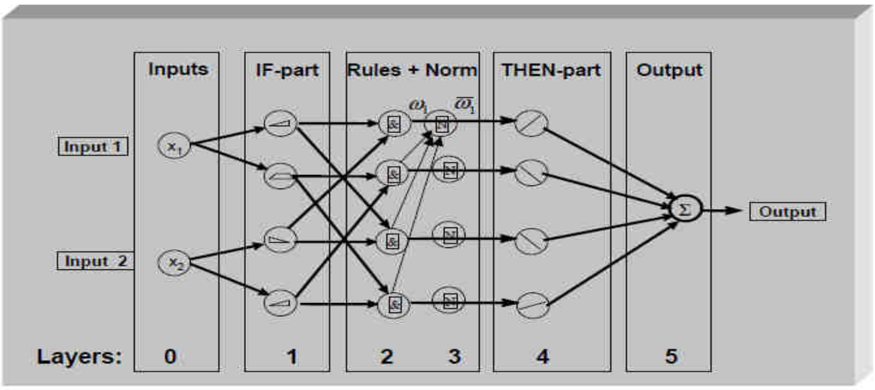


Fig 2: The general ANFIS architecture

Five network layers are used by ANFIS to perform the following fuzzy inference steps. (i) Input fuzzification, (ii) Fuzzy set database construction, (iii) Fuzzy rule base construction, (iv) Decision making, and (v) Output defuzzification.

For instance assume that the FIS has two inputs x_1 and x_2 and one output y. For the first order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

$$Rule\ 1: IF\ (x_1\ is\ A_1)\ AND\ (x_2\ is\ B_1)\ THEN\ f_1 = p_1x_1 + q_1x_2 + r_1 \quad \ldots..2$$

$$Rule\ 2: IF\ (x_1\ is\ A_2)\ AND\ (x_2\ is\ B_2)\ THEN\ f_2 = p_2x_1 + q_2x_2 + r_2 \quad \ldots.3$$

Where A_1, A_2 and B_1, B_2 are the membership functions for the input x_1 and x_2, respectively, p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function. The functioning of the ANFIS

Layer 1: Calculate Membership Value for Premise Parameter

Every node in this layer produces membership grades of an input parameter. The node output

$$o_{l,i} = \mu_{Ai}(x_1)\ for\ i = 1,2, or \quad \ldots.4$$

$$o_{l,i} = \mu_{Bi-2}(x_2)\ for\ i = 3,4 \quad \ldots.5$$

Where x_1 (or x_2) is the input to the node i; A_i (or B_{i-2}) is a linguistic fuzzy set associated with this node. $O_{1,i}$ is the membership functions (MFs) grade of a fuzzy set and it specifies the degree to which the given input x_1 (or x_2) satisfies the quantifier. MFs can be any functions that are Gaussian, generalized bell shaped, triangular and trapezoidal shaped functions. A generalized bell shaped function can be selected within this MFs and it is described as:

$$\mu_{Ai}(X_1) = \frac{1}{1 + \left|\frac{X_1 - c_i}{a_i}\right|^{2b_i}} \quad \ldots..6$$

Where a_i, b_i, c_i is the parameter set which changes the shapes of the membership function degree with maximum value equal to 1 and minimum value equal to 0.

Layer 2: Firing Strength of Rule

Every node in this layer, labeled Π, whose output is the product of all incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x_1)\,\mu_{Bi}(x_2) \text{ for } i = 1,2 \qquad \ldots\ldots 7$$

Layer 3: Normalize Firing Strength

The ith node of this layer, labeled N, calculates the normalized firing strength as,

$$O_{2,i} = \bar{W}_i = \frac{W_i}{w_1 + w_2} \quad i = 1,2 \qquad \ldots .8$$

Layer 4: Consequent Parameters

Every node i in this layer is an adaptive node with a node function,

$$O_{4,1} = \bar{W}_i f_i = \bar{W}_i\,(p_i x_1 + q_i x_2 + r_i) \qquad \ldots ..9$$

Where i is the normalized weighting factor of the iwth rule, f_i is the output of the ith rule and p_i, q_i r_i is consequent parameter set.

Layer 5: Overall Output

The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals:

$$\mathit{Overall\ output} = O_{5,i} = \sum_i \bar{W}_i f_i = \frac{\sum_i W_i f_i}{\sum_i W_i} \qquad \ldots ..10$$

ANFIS requires a training data set of desired input/output pair (x_1, $x_2 \ldots x_m$, y) depicting the target system to be modeled. ANFIS adaptively maps the inputs (x_1, $x_2 \ldots x_m$) to the outputs (y) through MFs, the rule base and the related parameters emulating the given training data set. It starts with initial MFs, in terms of type and number, and the rule base that can be designed intuitively. ANFIS applies a hybrid learning method for updating the FIS parameters. It utilizes the gradient descent approach to fine-tune the premise parameters that define MFs. It applies the least-squares method to identify the consequent parameters that define the coefficients of each output equation in the Sugeno-type fuzzy rule base. The training process continues till the desired number of training steps (epochs) or the desired root mean square error (RMSE) between the desired and the generated output is achieved. In addition to the training data, the validation data are also optionally used for checking the generalization capability of ANFIS. the results for the network with three membership functions.

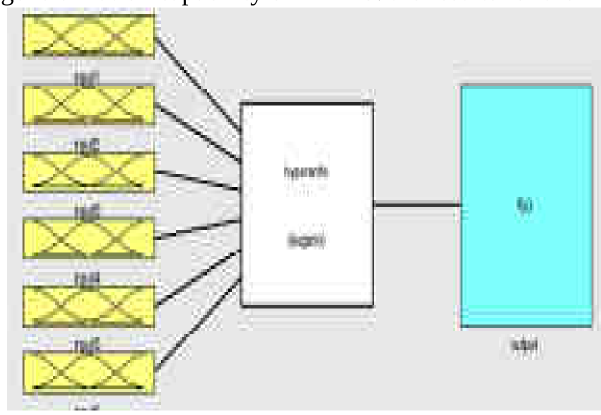


Fig 3: Scheme of the ANFIS network

Fig 4: The main Interface of the System

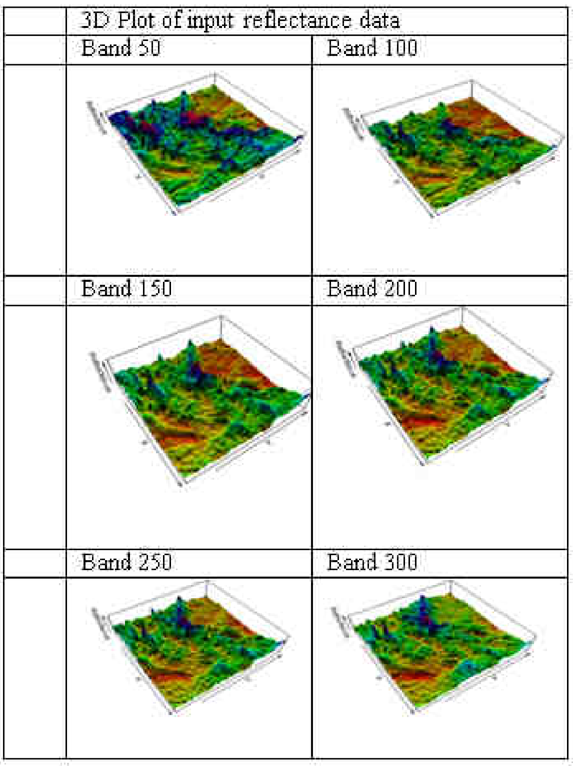


Fig 5: 3D Plot of input reflectance data

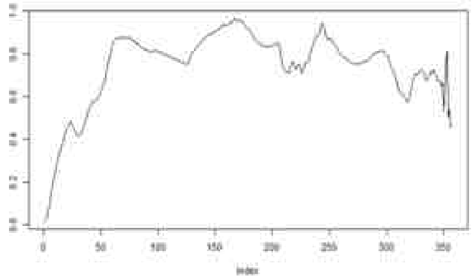


Fig 6: The spectrum of a pixel

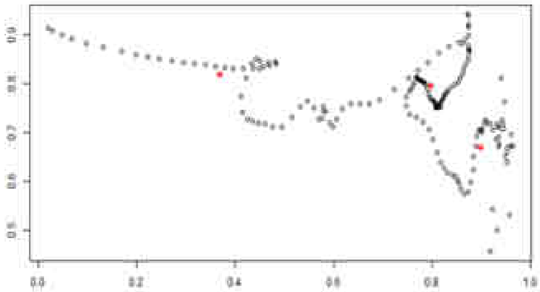


Fig 7: Clustered image of a pixel with 3 Cluster centers shown in red

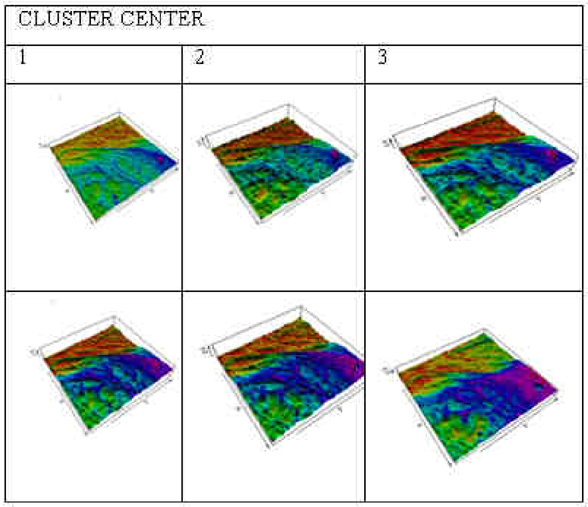


Fig 8: 3D Plots of the cluster center data

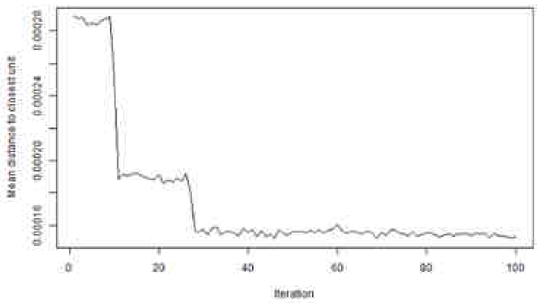


Fig 9: Training Progress of KSOM

Fig 10: 3D Plots of the cluster center data

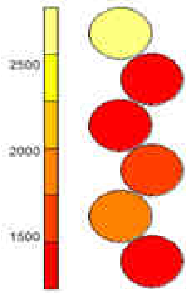
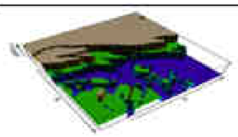
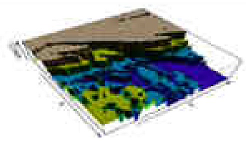
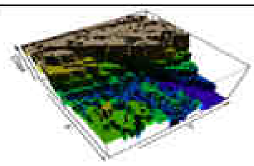
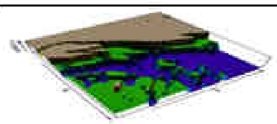
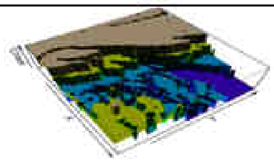
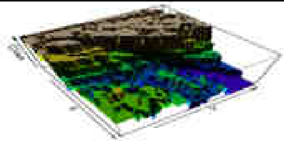


Fig 11: Class count plot of trained KSOM

	PREDICTED SOIL MAP		
	3 classes	4 classes	6 classes
CC1			
CC2			

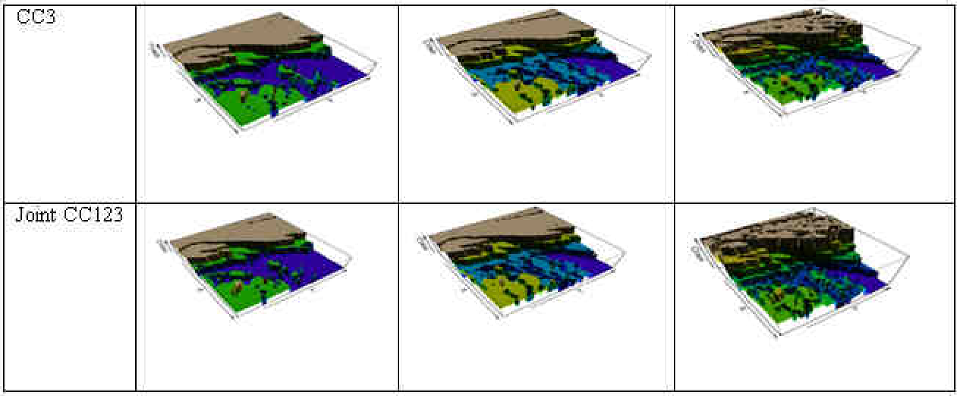


Fig 11: 3D Plots of the predicted soil maps

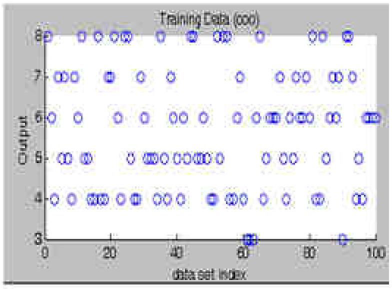


Fig 12: Training data set for ANFIS network

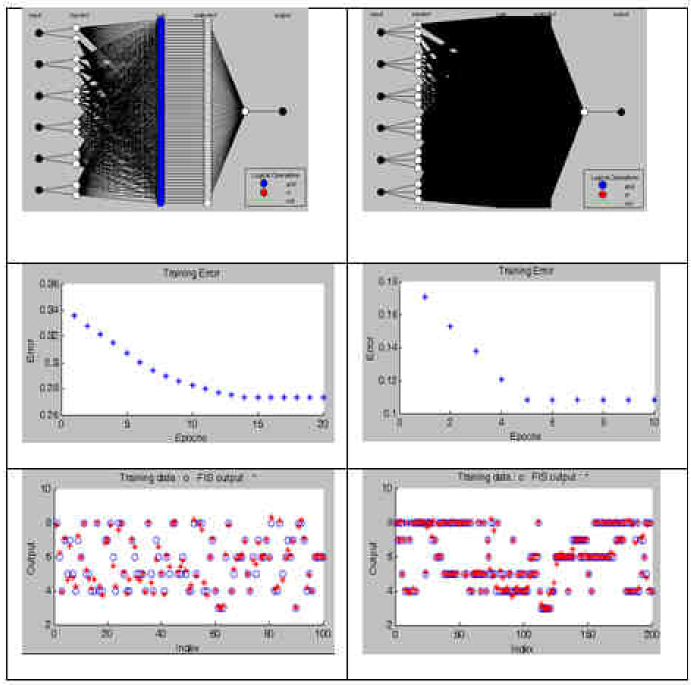


Fig 13: Comparison of performance of ANFIS network with 2 or 3 membership functions

With three membership function, the network learnt to classify the samples with approximately zero error level within 20 epochs as shown in Fig 13. Test with original training sample shows a 100% score as shown by all the red marks inside blue in Fig 13.

Novel soil

In Fig 13, it can be noticed that soils in a particular class are aligned on a straight line. If a sample for a novel soil (not yet learned soil) is presented to the network, the output for it will not fall on an already existing line. This is an indication that the presented sample is a novel mineral. In such case, further samples needs to be presented and the system allowed to learn the new sample.

The ANFIS network learns and store knowledge as rule base. This rule base can be variously visualized as shown in fig 14 or as rule surfaces that shows how inputs combine with one another as shown in Fig 15. Also the shape of the membership functions change as the system learns as depicted in Fig 16.

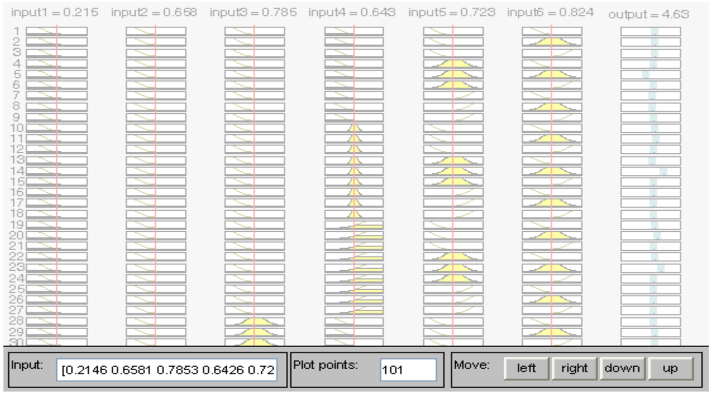


Fig 14: Rule base of the trained network

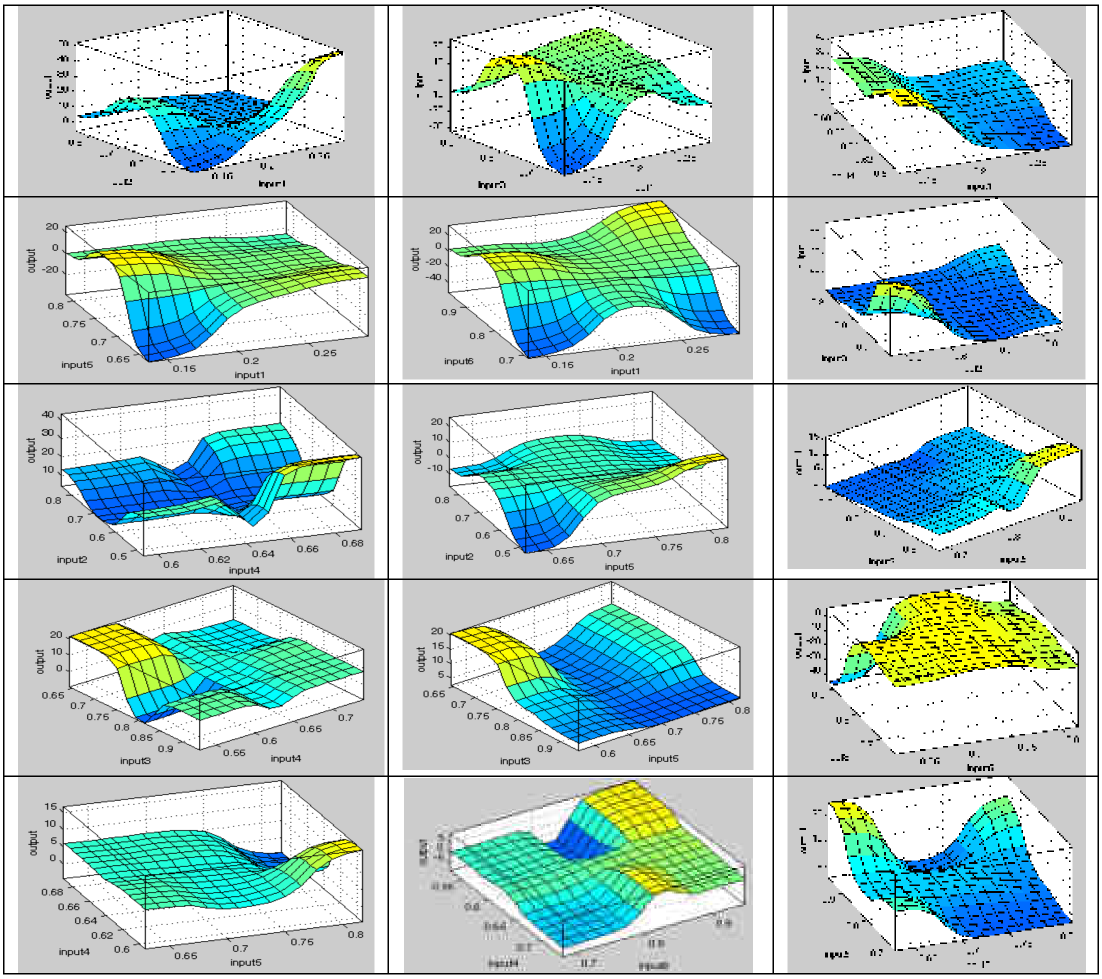
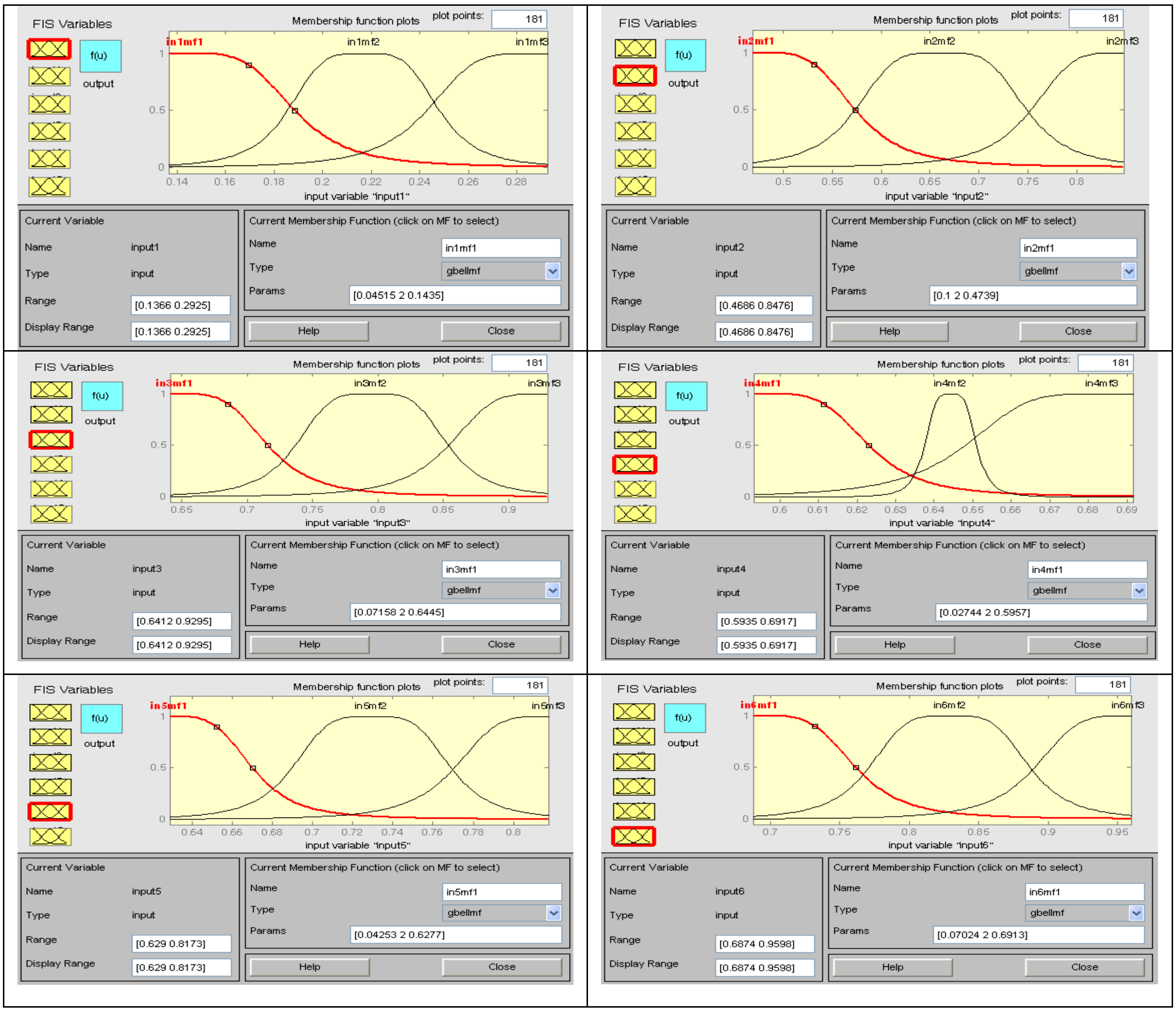


Fig 15: Rule surfaces of the trained network



7. Methodology

3D plot of input reflectance data at bands 50, 100,150,200,250,300 were obtained as shown in fig 5. The spectrum of a pixel is obtained as indicated in fig 6. The pixel was processed using halving method which was then clustered using fuzzy C-means to obtain cluster image with 3 cluster centres shown in red in fig 7. The 3D image of the cluster centres are shown in fig 8. The cluster centres are used to train a Kohonen self organizing map to generate soil prediction map which was used as an output in the training of ANFIS. The training progress of the KSOM is expressed in fig 9. Also, the 3D plot of the cluster centre data generated by KSOM and its soil class count was shown in 10 and 11 respectively. Figure 12 explained the training of dataset for the ANFIS network.

2 membership functions and 3 membership functions are used to train the ANFIS as shown in fig 13. With 2 membership function, the error is on the high side and the training data missies their target. With 3 membership function, the situation is better as show in fig 13. So, the 3 membership function was adopted. Fig 14 shows the rule based of the trained network while fig 15 showed the rule surface of the trained network.

The graphical illustration of the membership function of the trained network is shown in fig 16 and fig 17 shows the abundance volume estimation for 4 classes of the soil while fig 18shows the abundance volume estimation for 6 classes.

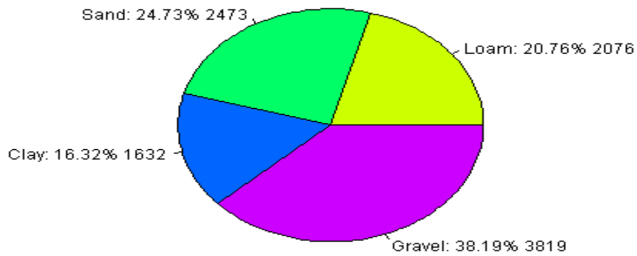


Fig 16: Abundance Volume Estimation for 4 classes

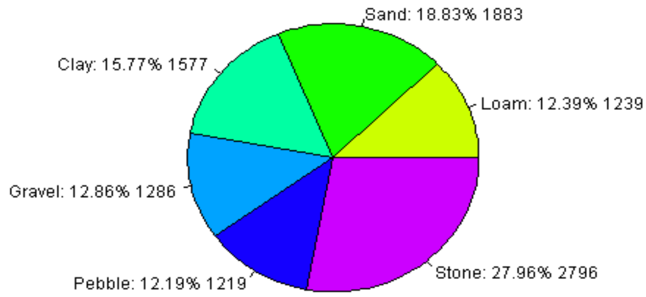


Fig 17: Abundance Volume Estimation for 6 classes

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