SOIL MOISTURE ESTIMATION BY ANN USING BISTATIC SCATTEROMETER DATA

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ABSTRACT:

The microwave response of bare soil surfaces is influenced by a variety of parameters such as surface roughness, vegetation density, soil texture and soil moisture. It makes the soil moisture estimation process more complex. In such condition, the estimation of the soil moisture using microwave data with fast and less complex computing technique is a significant area of research today. The artificial neural network (ANN) approach has been found more potential in retrieving soil moisture from microwave sensors as compared to traditional techniques. For this purpose, a back propagation artificial neural network (BPANN) based on Levenberg Marquardt (TRAINLM) algorithm was developed. The measurement of scattering coefficient was carried out over a range of incidence angle from 20° to 70° at 5° steps for both the HH- and VV- polarizations. The BPANN was trained and tested with the experimentally obtained data by using bistatic X-band scatterometer for different values of soil moistures (12%, 16%, 21% and 25%) at 30^0 incidence angle. The scattering coefficient and soil moisture data were interpolated into 20 data sets and these data sets were divided into training data sets (70%) and testing data sets (30%). The performance of the trained BPANN was evaluated by comparing the observed soil moisture and estimated soil moisture by developed BPANN using a linear regression analysis (least square fitting) and performance factor Adj_R^2. The values of Adj_R^2 were found 0.93 and 0.94 for HH- and VV- polarization at 30^0 incidence angle respectively. The estimation of soil moisture by BPANN with Levenberg Marquardt training algorithm was found better at both HH- and VV- polarizations.

1. INTRODUCTION

An accurate quantitative estimation of soil moisture at regional/global scale is a necessary factor for the land process mode, which plays a significant role in improving regional and global climate models, monitoring drought, estimating crop yields and investigating nature and eco-environment.

The soil moisture status is an important input to models quantifying the exchange of energy and matter between the land surface and the atmosphere. The knowledge of their spatial and temporal distribution is highly useful for regional or global-scale (Houborg et al., 2007). There are some limitations in traditional measurement methods of soil moisture. The microwave remote sensing is one of the most promising approaches to assess the surface parameter and moisture content because of its sensitivity to the dielectric and geometric characteristics of objects and its penetration capability (Guoliang, 1991).

The theory behind retrieval of soil at microwave frequencies is based on large dissimilarity between the dielectric constant of dry soil (~ 4) and water (~ 80) whereas the dielectric constant of soil-water mixture varies between 4 to 40. This variation of dielectric constant of soil-water mixture is detectable at microwave frequencies.

Several researchers have been reported radar measurement for the estimation of soil moisture (Jackson and Schmugge, 1991; Jackson et al., 1999; Liu et al., 2002; Meade et al., 1999; Njoku and Li, 1999; Srivastava et al., 2009; Tsang et al., 2004; Ulaby et al., 1981a; Ulaby et al., 1981b; Wang et al., 1983; Wigneron et al., 1995). The soil moisture and the radar backscattering have a complicate and non-linear relationship mostly because the dynamics of soil moisture is influenced by a variety of environmental factors, e.g. surface roughness, soil texture and density of vegetation(Lakhankar et al. 2006).
Many previous researchers have made physical, semi-empirical and empirical models for the estimation of soil surface

parameters (soil moisture, soil roughness and soil texture) using ground based, air borne and space borne radar data (Chang et al., 1980; Chen et al., 1995; Dubois et al., 1995; Fung et al., 1992; Jackson et al., 1981; Njoku et al., 2003; Oh et al., 1992; Ulaby and Batlivala, 1976; Ulaby et al., 1978; Ulaby et al., 1982). These models are very complex and cannot be simplified into simple linear equation. As its complexity needs to have non-parametric tools like artificial neural network and fuzzy logic for establishing the relation between soil moisture and microwave scattering coefficient for the estimation of soil moisture.

Artificial neural network is the most important technique in the field of hydrology since last few decades for the estimation of soil surface parameters from remotely sensed data. The artificial neural network have learning ability from environment and non-parametric in nature (Baghdadi et al., 2002; Chai et al., 2008; Chang and Islam, 2000; Del Frate et al., 2003).

There are two main objectives of the present work. First, the critical analysis of bistatic microwave response of bare soil surfaces with different moisture contents at different incidence angles for both like polarizations (HH & VV) at *X*-band. This analysis may be useful to predict the suitable bistatic radar configuration to retrieve soil moisture contents of bare soil surfaces. Second is to develop a back propagation artificial neural network using Levenberg Marquardt training algorithm for the estimation of soil moisture.

2. EXPERIMENTAL DATA

An outdoor experimental site of bare soil surface of area 4m × 4m was prepared. The specifications of bistatic scatterometer system are given in Table 1. The microwave bistatic measurements were carried out at 10 GHz frequency beside the Department of Physics, Indian Institute Technology (B.H.U), Varanasi, India. For this purpose, an X-band bistatic scatterometer setup was developed. It was capable of taking observations at different incidence angle ranging 20^0 to 70^0

steps of 5^0 and both like polarizations (HH- and VV-polarization).Two pyramidal horn antennas were used for transmitting and receiving the microwave energy having the gain 20 dB and half power beam width 18^0 and 20^0 for E- and H- plane respectively. The 90^0 E-H twisters were used to change the polarization HH- to VV- and vice-versa. The scatterometer system had facility of changing the height and distance from the centre of target to focus the both antennas at the centre of target. The antennas were placed in far field region from the centre of the target to minimize the near field interactions.

This system was calibrated by noting the signals returned from an aluminum plate. The measurements were carried out for all possible angles, keeping an aluminum plate on the target. Then, the plate was removed and angular measurements of bistatic response from the bare soil were carried out. The calibration of system was done regularly during the experiment to ensure the integrity of the system.

The soil moisture conditions were different however the surface roughness was tried to maintain smooth and constant during the entire observations. The gravimetric moisture content of soil is defined as ratio of weight of water present in soil to weight of dry soil and it is expressed in the percentage of soil moisture content. Five randomly soil samples were collected in the aluminum soil containers up to depths of 5 cm from soil surface. These soil samples were dried in an oven at 100 ^{0}C for 24 hour. The samples were weighted before and after drying and computed the gravimetric moisture content. The average of gravimetric moisture content of all five soil samples were taken to calculate the percentage of soil moisture content of soil surface.

RF generator	Agilent Technologies – E8257D
Power sensor	Agilent Technologies – E9372A
Central frequency of the system	10 GHz
Antenna type	Dual Polarized Pyramidal Horn
Antenna gain	20 dB
Platform height	3 m
Incidence angle	20^0-70^0
Polarization modes	HH- and VV-
Cross polarization isolation	40dB

TABLE 1. Specification of scatterometer system

3. RESULTS AND DISCUSSION

3.1 Angular response of scattering coefficient

Figures 1 and 2 show the angular variation of scattering coefficient at different soil moisture conditions (12%, 16%, 21% and 25%) for HH- and VV-polarization respectively. The surface roughness was tried to maintain smooth and constant to study the microwave response of soil moisture variation during entire observation. The dynamic ranges of angular variation of scattering coefficient with different moist soil surfaces were found to be 6.79 dB and 10.68 dB for HH- polarization and VV- polarization respectively. The scattering coefficient was found to increase with the soil moisture content. Similar results have been obtained by (Dobson and Ulaby, 1981; Ulaby et al., 1982) and (Bertuzzi et al., 1992). The maximum scattering

coefficient was found at highest percentage of soil moisture (25%). All the scattering coefficient curves were found to decrease monotonically with the incidence angles. It is due to increase of dominant contribution of volume scattering at higher incidence angles. Thus, the separation between the scattering coefficients at higher incidence angles decreases. It is due to the fact that surface appears smoother at higher incidence angles. Therefore, VV-polarization and lower incidence angle may be suitable for the estimation of soil moisture. In this study, the scattering coefficient at 30^0 incidence angle and VV-polarization was taken for training and testing of developed ANN for the soil moisture estimation.
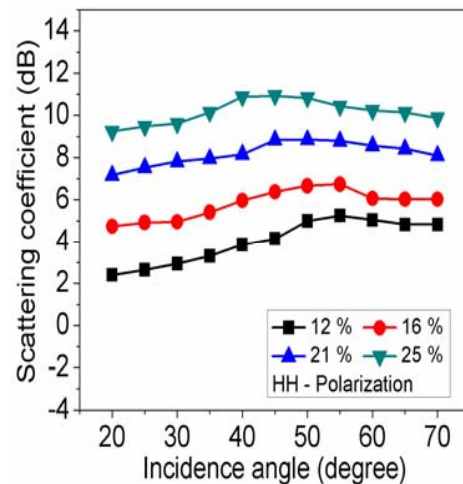

Figure 1. Angular variation of scattering coefficient at HH- polarization
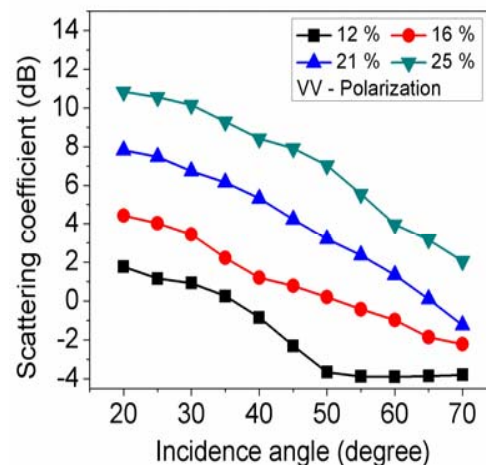

Figure 2. Angular variation of scattering coefficient at VV- polarization

3.2 Estimation of soil moisture using ANN

A multi-layer back propagation artificial neural network having, simple processing units (neurons) are arranged in different layers as input, hidden and output layers. These layers are fully interconnected. The input to one node is the weighted sum of the outputs of the previous layer nodes. This sum is passed through an activation function to produce the final output. The activation function is usually a sigmoid or hyperbolic tangent, which are non-linear functions that have an asymptotic behaviour (Rumelhart et al., 1986). The training stage consists of adjusting the connection weights (randomly initialized) in order to decrease the difference between the network output and the desired outputs. The training data were presented to the input layer and propagated through the hidden layer to the

output layer. The differences between the computed and the desired outputs were computed and feed backwards to adjust the network connections. This iterative process continued until the root mean square error reached at desired level. When the root mean square error reached at optimum level, the training is stopped and the weight and bias values saved. The trained network was used for the estimation of soil moisture condition of bare soil surfaces.

The observed data set (scattering coefficient and soil moisture) were interpolated to 20 data sets at 30^0 incidence angle for both like polarizations (HH- & VV-). The 70% data sets were used for training and remaining 30% data sets were used for the testing of BPANN. The training and testing data sets were randomly selected.

In this study, MATLAB software was used for developing a BPANN consisting of one neuron at input layer, five neurons at hidden layer and one neuron at output layer. Sometimes, it is called as [1:5:1] architecture of BPANN as shown in Figure 3. The hyperbolic tangent sigmoid transfer function (tansig) was used for input and hidden layer whereas linear transfer function (purelin) was used for the output layer. The BPANN was trained using input data (scattering coefficient) and target data (soil moisture content). The developed BPANN was used for testing.

Remaining 6 data sets out of 20 data sets were used for testing the developed and trained BPANN. The performance function Adj_R^2 was used for testing the performance of developed BPANN at 30^0 incidence angle for both like polarization at X-band. The performance function Adj_R^2 shows high correlation between estimated and observed soil moisture data.

Figures 4 and 5 show the linear regression results between the estimated values of soil moistures by ANN and observed soil moisture for HH- and VV- polarization respectively at 30^0 incidence angle. The high values of Adj_R^2 were found 0.93 and 0.94 for HH- and VV- polarization respectively. However, higher value of Adj_R^2 was found by VV- polarization as compared to HH- polarization.
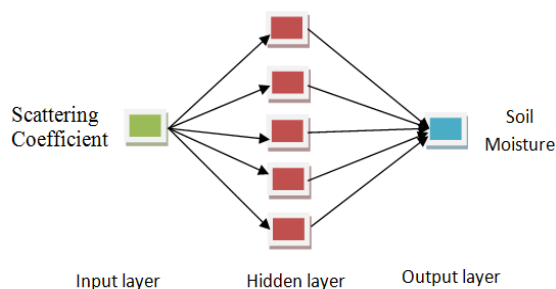

Figure 3. Architecture of BPANN used in the study.

CONCLUSIONS

The bistatic microwave scattering coefficient was found to increase with the soil moisture content. The dynamic range of scattering coefficient was found more at VV- polarization than HH-polarization. The estimation of soil moisture of bare soil surfaces by BPANN was found to provide better results at both HH- polarization and VV- polarization.
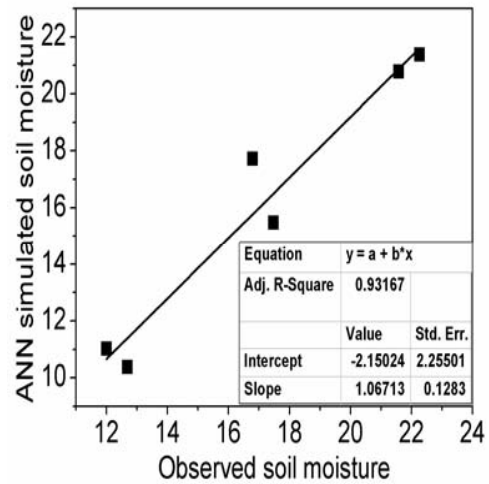
Figure 4. ANN simulated soil moisture Vs observed soil moisture at HH - polarization
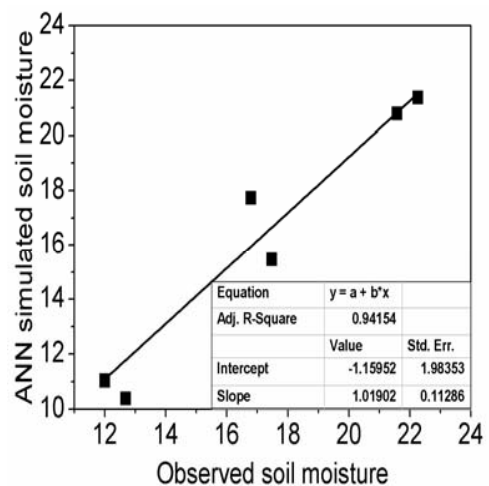

Figure 5. ANN simulated soil moisture Vs observed soil moisture at VV - polarization

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