Progress In Electromagnetics Research B, Vol. 15, 245–265, 2009

APPLICATION OF NEURAL NETWORK WITH ERROR CORRELATION AND TIME EVOLUTION FOR RETRIEVAL OF SOIL MOISTURE AND OTHER VEGETATION VARIABLES

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Abstract—Present paper utilizes the time evolution for estimating the soil moisture and vegetation parameter with radar remote sensing data. For this purpose, vegetation ladyfinger has been taken as a test field and experimental observations have been taken by bistatic scatterometer at X-band in the regular interval of 10 days for both like polarizations (i.e., Horizontal-Horizontal, HH-; Vertical-Vertical, VV-) and at different incidence angles. At this interval, all the vegetation parameters and scattering coefficient have been recorded and computed. Three similar types of field of size 5×5 m have been especially prepared for this purpose. The observed data is critically analyzed to understand the effect of incidence angle and polarization effect on scattering coefficient of the ladyfinger. It is observed that VV-polarization gives better result than HH-polarization and incidence angle 55° is the best suited to observe composite effect of vegetation ladyfinger biomass (Bm) and vegetation covered soil moisture at X-band. This analysis is further used for retrieval of soil moisture and

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biomass of ladyfinger using Neural Network. The important aspect of the retrieval algorithm is that it includes the time evolution. The retrieval results for soil moisture and Bm are in good agreement with the actual values of the soil moisture and biomass.

1. INTRODUCTION

Remote sensing is typically defined as the art and science of acquiring information about objects without physical contact with the objects. It is a contemporary and constantly improving scientific technology that can be applied to observe, monitor, and measure critical biophysical parameters and characteristics, as well as human activities on the earth. As its technology has become mature, its important role to human beings is increasingly recognized and emphasized. For the last three four decades, important advances have been made towards the application of the passive microwave remote sensing to measure land surface parameters, especially soil moisture and crop biomass.

Ladyfinger is an annual vegetative crop grown from seeds in tropical and subtropical parts of the world. It is cultivated throughout India for its immature fruits that are generally cooked as vegetable. Ladyfinger (Botanical name of ladyfinger is *Abelmoschus esculentus, L*, *Moench* and *in* Hindi *"BHINDI"*) soups and stews are also popular dishes. When ripe, the black or brown white-eyed seed are sometimes roasted and used as a substitute for coffee in Turkey. The roots and stems of ladyfinger are used for cleaning the cane juice from which brown sugar is prepared. In some places the plants are soaked in water and the resulting solution is used as a purifier in the manufacture of jaggery. The crop is used in paper industry and stem of the plant is used for extraction of fiber. Ladyfinger is, thus, a very important horticulture vegetation of our country.

Crop/vegetation monitoring during regular interval is essential to take appropriate measure and to assess information on probable loss in production. Horticulture crop covers an estimated 6.8% of the geographical area of our country and contribute to 18% of India's gross agriculture for food industry. Special efforts are needed to utilize the space-based remote sensing technology for generating information required for horticultural crop/vegetation. Every kind of vegetation has its own importance for living beings and shows different types of behavior with microwaves.

A lot of radar measurements have been reported in literature for vegetation covers on the earth, still much more to explore. There is a great interest in the interpretation of radar measurement of vegetation and in development of models to classify and estimate, invert the response from different vegetation kinds. Applications of these classification techniques include crop monitoring, estimation of biomass, crop classification etc. During the last decade, many techniques for vegetation classification and monitoring were reported [1–18]. Since scattering mechanism depends on the physical structure of the target, kind of vegetation, with different morphology could be contrasted and, more over, physical parameters (i.e., LAI, biomass, plant height etc.) of the vegetation like ladyfinger could be estimated. However, inconsistencies exist in level of significance, strength of correlation of a particular parameter identified by various researchers [9, 13]. This is due to the complex inter-relationship between system and target parameters and difficulty in making enough accurate measurements of various parameters in experimental studies. Although many vegetation parameters have been addressed so far, uncertainties still exist as to which vegetation parameter is more important for radar scattering. The challenge is to acquire the data in such a fashion and with the appropriate radar parameters, so as to minimize the dependence of radar scattering on all the parameters except those related to the vegetation.

For forecasting the vegetation field and crop classification, biomass is one of the most important parameter, which gives significant results [6]. Soil moisture underneath vegetation holds key to proper growth at every stage. Therefore, for comprehensive monitoring and yield prediction, soil moisture information is an important parameter. It is also an important input to vegetation development models. The procedure to reliably relate the radar scattering to soil moisture at the surface and subsequently, relate this information to the lower layer of soil needs to be refined.

Direct application of the scattering coefficient for biomass retrieval is limited by saturation [18]. The saturation of leaves is dependent on seasonal and weather conditions, which suggests the use a multi temporal data for biomass and soil moisture retrieval.

The main aim of this paper is, therefore, to critically analyze the microwave response of ladyfinger and to apply it to retrieve vegetation covered soil moisture and ladyfinger biomass. Radar data were acquired at X-band operating in different configurations of polarization (HH- and VV-) and incidence angle. A model describing the relationships between scattering coefficient and soil moisture and other vegetation variables is developed in which electromagnetic modeling using multilayer neural network has been used. The method is based on simultaneous retrieval of soil moisture by means of inverting a theoretical scattering model using multiple layer artificial neural network (ANN). First, results of surface soil moisture retrieval are analyzed, using data collected from the scatterometer. Promising results for retrieved soil moisture confirm the validity of the proposed method.

There are two obvious purposes of the present work. First, critical analysis of microwave scattering by ladyfinger at X-band for different incidence angles for like polarizations (i.e., HH, Horizontal-Horizontal; VV-, Vertical-Vertical). This analysis becomes a useful tool in deciding the better polarization and the best suited incidence angle to retrieve ladyfinger parameters. Second is to develop a Back Propagation Neural Network with Error Correlation that incorporates a novel rule, error correlation learning, to train a feed forward neural network [1, 7, 8] for estimating the ladyfinger parameters (i.e., biomass and vegetation covered soil moisture). The main objective is to provide an alternative way to estimate the soil moisture and important vegetation variables, such as biomass through neural network. Three main steps of the present work are 1) to adopt a suitable radar configuration, 2) to establish a reliable relationship between the scattering coefficient (σ_c°) and the field variables, 3) to retrieve the parameters from trained network (to solve inverse problem).

2. EXPERIMENTAL SETUP

Figure 1 illustrates the schematic representation of the scatterometer. Two pyramidal horn antennas (one connected to the transmitter side and the other on the receiver side, having half power beam widths 19° and 22° in E-and H-plane, respectively, with a gain of 20 dB, operating at 9.52 GHz, were mounted on a specially designed portable stand. The height and look angle of the antennas mounted on a platform on this stand can be varied. The height and look angle can be read from the graduated linear and circular scales with pointers provided on the stand. The polarization of the radiated signal is changed by using 90° E-H twist. The look angle of microwave signals is systematically changed and the reflected components of the signals from the target under investigation are located. Great care has been taken to avoid stray reflections under experimental conditions by putting a 30 dB microwave absorber to the exposed parts. The antennas were always placed, at least, one meter away from the calculated far-field region from the centre of the target to minimize the near-field interactions.

The overall system was calibrated by noting the signals returned from an aluminum plate placed on the top of the target surface. To ensure that the transmitted power is low enough for operation of the detectors in square-law region, a known amount of loss (in dB) was introduced through the attenuator in the transmitting arm. It is observed that the meter connected to the receiving antenna displays the same amount of the introduced loss. This ensures the detector's operation in the square-law region.

After this important check, measurements were carried out for all possible angles, keeping an aluminum plate on the target. Then, the plate was removed and angular measurements for the target were carried out. The system was calibrated for the direct view of the transmitter and receiver, also. The calibration of the system was done regularly during the experiment to ensure the integrity of the system. Various scatterometer parameters are listed in Table 1. Other details are given in [14, 18].

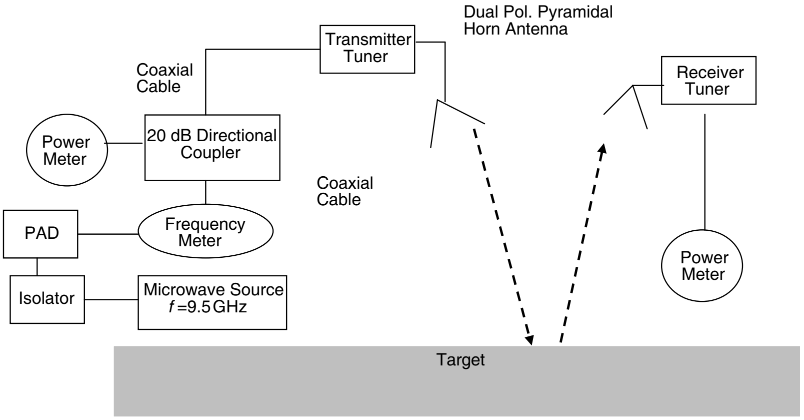

Figure 1. Schematic diagram of scatteromemter.

Table 1. Scatterometer parameter.

Central Frequency	9.5 GHz
Frequency Band Width	0.8 GHz
Antenna type	Dual Polarized Pyramidal Horn
Antenna Beam Width	8.5 degree
Antenna Gain	20 dB
Platform Height	3 m
Cross-pol Isolation	40 dB
Calibration Accuracy	1 dB

3. RESULTS AND DISCUSSION

3.1. Field Data Synthesis

Three outdoor fields of $5\,\mathrm{m} \times 5\,\mathrm{m}$ had been prepared for observation. Ladyfinger is narrow leaf vegetation which was planted in first week of September. The irrigation was done in every six days. The observations of ladyfinger were taken every ten days of interval up to 90 days of sowing. The vegetation attained the maximum average height of around 51 cm in our vegetation bed. The fruit filing stage of this ladyfinger arrived at around 48–50 days from the date of sowing.

Table 2 shows the temporal variation of biomass and vegetation covered soil moisture (gravimetric). It is observed that during 30 to 60 days after sowing the noticeable amount of change in ladyfinger biomass has been observed while as field is irrigated every six days of interval. It can be concluded that during entire period of observation, ladyfinger biomass and soil moisture varied noticeably but change in biomass is not very much because ladyfinger is vegetation and life period of ladyfinger is less and growth of plant is not too much i.e., approximately after 60 days of sowing in this field.

The gravimetric moisture content of soil is defined as ratio of water present in soil to weight of dry soil and is expressed as percentage of soil moisture content. The total biomass has been computed from sample stalks and leaves were dried in oven at 80°C for 24 hours. The samples were weighed before and after drying and weight per square meter has been computed. The biomass of the plant gives an idea of total dry matter accumulation in the complete plant body over a period of time.

Table 2. Field parameters of ladyfinger (reference field).

Age	LAI	Biomass(kg m^{-2})	SM
30	0.89	0.69	27.8%
40	1.54	0.83	26.4%
50	2.68	1.33	25.5%
60	4.91	1.69	21.7%
70	5.76	1.78	22.9%
80	6.27	1.83	23.6%
90	6.65	1.84	21.5%

* LAI-Leaf area index, Biomass-Bm, SM-percentage of soil moisture (gravimetric)

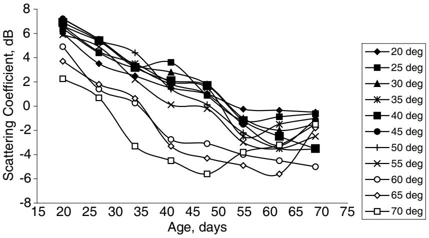

Figure 2. Temporal variation of scattering coefficient of ladyfinger for HH-pol.

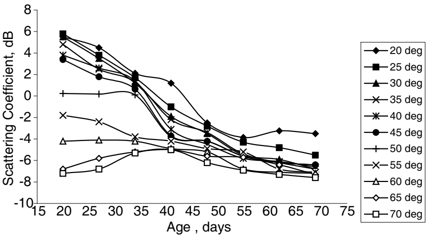

Figure 3. Temporal variation of scattering coefficient of ladyfinger for VV-pol.

3.2. Temporal Variation of Scattering Coefficient

Figures 2 and 3 show the temporal variation of scattering coefficient of ladyfinger at X-band for different incidence angles i.e., ($\theta = 20^\circ$ to 70°) for HH-pol and VV-pol, respectively. It is observed from both the figures that scattering coefficient typically shows decreasing behavior at most of the incidence angles. The decreasing trend of σ° with age may be attributed to the fact that microwave interaction with vegetation covered soil is less in the later age because vegetation is approximately covered the ground. Average variation of σ° with age (from 20 days to 69 days) is 7.19 dB for HH-polarization and 8.62 dB for VV-polarization. These figures show that the scattering coefficient generally decreases with age for both HH- and VV-polarization and the decrease is more for lower incidence angles (Figure 2 and Figure 3). It may be because at lower incidence angle microwave interacts with vegetation covered ground as well as vegetation more prominently while as at higher incidence angle the microwave scattering is prominent by vegetation itself [18]. It can also be observed from Figures 2 and 3 that σ° has maximum value during the initial stage of growth and at 20° incidence angle for both like polarization. The semi planophile leaves of ladyfinger contribute much to volume scattering. Thus, the angular effect on σ° at each stage of growth of ladyfinger is significant. The typical strong temporal variation of scattering coefficient from ladyfinger plant observed for both like polarizations at X-band, is higher than that reported for soybean, corn and wheat at C-band [5, 17]. The nature of variation at middle incidence angle i.e., $30^\circ < \theta < 50^\circ$, quite similar to the trend obtained by Kim et al. [9] for rice crop at X-band.

3.3. Statistical Analysis

To examine the effect of individual crop parameter viz. biomass (Bm) and soil moisture (SM) on scattering coefficient at different incidence angles, partial regression analysis is done which is based on the following equation for scattering coefficient in dB

$$\sigma^\circ(\theta, p) = a_1\mathrm{SM} + a_2 Bm + a_3 \quad (1)$$

where a_1, a_2 and a_3 are constants.

The regression results for HH-polarization are shown in Table 3. It is evident that the dependence of σ° on soil moisture is more at lower incidence angle (i.e., 20°, $R^2_{\mathrm{SM}} = 0.860$) and on biomass at higher incidence angle (i.e., 50°, $R^2_{\mathrm{BM}} = 0.798$).

The partial regression results for VV-polarization are given in Table 4 which shows the similar trend as HH-polarization i.e.,

Table 3. Angular variation of partial regression results for HH polarization.

Angle (°)	Biomass			Soil Moisture		
	R	R^2	SEE	R	R^2	SEE
20	0.765	0.586	1.57	0.928	0.860	0.91211
25	0.822	0.675	1.73745	0.757	0.572	1.99422
30	0.846	0.716	1.93473	0.740	0.574	2.44462
35	0.824	0.679	1.94054	0.785	0.616	2.12248
40	0.845	0.715	2.13576	0.739	0.546	2.69373
45	0.850	0.723	2.04334	0.722	0.522	2.68453
50	0.894	0.798	1.95993	0.797	0.635	2.63812
55	0.880	0.774	1.83230	0.782	0.612	2.40324
60	0.778	0.606	2.34927	0.775	0.600	2.33254
65	0.780	0.608	2.30844	0.663	0.440	3.3658

Table 4. Angular variation of partial regression results for VV polarization.

Angle (°)	Biomass			Soil Moisture		
	R	R^2	SEE	R	R^2	SEE
20	0.720	0.519	2.65978	0.826	0.683	2.16037
25	0.767	0.588	2.98146	0.924	0.853	1.78065
30	0.879	0.772	2.37529	0.791	0.625	3.04713
35	0.868	0.753	2.32685	0.777	0.604	2.94504
40	0.898	0.807	2.01160	0.818	0.670	2.62843
45	0.876	0.768	2.02649	0.787	0.619	2.59367
50	0.915	0.837	1.28089	0.839	0.704	1.72809
55	0.846	0.716	1.08673	0.804	0.646	2.2634
60	0.878	0.771	0.70258	0.814	0.663	0.85144

Table 5. Regression results of composite effect of all plant parameters.

Angle(°)	HH-Polarization			VV-Polarization		
	R	R^2	SEE	R	R^2	SEE
20	0.937	0.878	1.046	0.937	0.878	1.639
25	0.947	0.896	1.203	0.934	0.872	2.036
30	0.974	0.949	1.067	0.973	0.946	1.419
35	0.943	0.888	1.401	0.972	0.945	1.342
40	0.993	0.985	0.594	0.959	0.919	1.594
45	0.948	0.899	1.508	0.949	0.901	1.620
50	0.984	0.968	0.958	0.963	0.927	1.054
55	0.952	0.907	1.440	0.998	0.995	0.174
60	0.921	0.848	1.785	0.966	0.933	0.446
65	0.804	0.646	2.688	0.361	0.130	0.980
70	0.549	0.302	2.954	0.419	0.176	1.145

dependence of σ° on soil moisture is more at lower incidence angle (i.e., 25°, $R^2_{\mathrm{SM}} = 0.853$) and on biomass at higher incidence angle (i.e., 50°, $R^2_{\mathrm{BM}} = 0.837$).

The composite effect of both the vegetation parameters, biomass and vegetation covered soil moisture on scattering coefficient is carried out using Eq. (1) and the results are given in Table 5 for various incidence angles. This table shows that both the polarizations give equally good results up to 60° incidence angle but VV-polarization is the most suitable at 55° because the value of R^2 is maximum at this angle for VV-polarization in comparison to HH-polarization.

3.4. Retrieval Algorithm

The procedure has been structured into several steps as given in flow chart Figures 4 and 5. Various steps are discussed in the following sections.

To train the neural network, a well established algorithm to assess the crop covered soil moisture and ladyfinger biomass is applied.

3.4.1. Step 1: Models for Soil Moisture and Vegetation Biomass

An observation with scatterometer has been carried out for bare field (5×5 m) where it is assumed that soil texture and moisture condition is approximately same as ladyfinger field. This observation is useful to develop a relationship with scattering coefficient and soil moisture (SM) [18]. The following relationship has been obtained

$$\sigma^\circ(\theta, p) = K_1 \cdot (\mathrm{SM}) + X \tag{2}$$

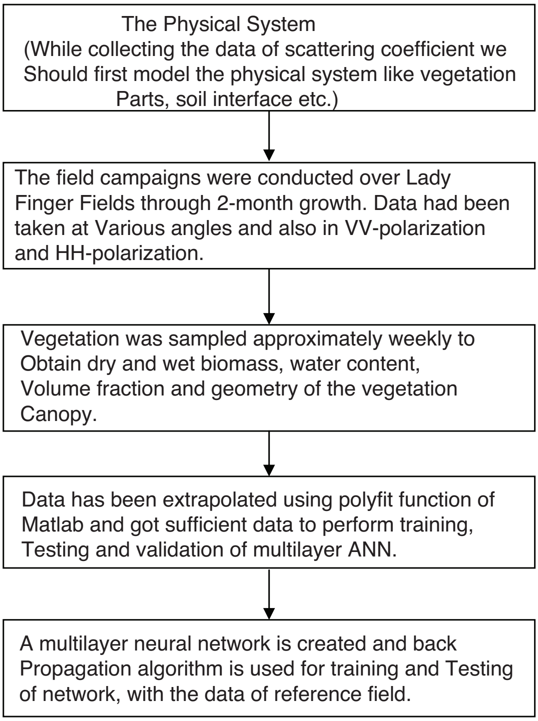

Figure 4. Flow chart of algorithm used.

where SM is percentage of gravimetric soil moisture, K_1 is a slope, and X is a noise factor which includes system as well as observation noise.

Similarly, a relationship between vegetation parameter i.e., biomass (Bm) and scattering coefficient has been applied as given below.

The scattering coefficient of ladyfinger (σ°) can be represented as

$$\sigma^\circ(\theta) = \sigma_c^\circ + t^2\sigma_g^\circ \tag{3}$$

where, σ_c° is the scattering coefficient by ladyfinger vegetation, t is the ladyfinger plant transmitivity, σ_g^0 is the scattering coefficient of the vegetation cover soil. The Eq. (1) was analyzed and solved by Pulliainen et al. [12], and observed that the scattering coefficient in crop is dominated by biomass and gave the following empirical relation for σ° [12]

$$\sigma^\circ = \frac{C_1}{-2C_2}\left(1 - e^{2C_2Bm}\right) + C_3e^{2C_2Bm} \tag{4}$$

Where, first part of Eq. (4) represents the scattering component of the vegetation and the second part of (4) is ground scattering component, Bm is the vegetation biomass, the parameters C_1 and C_2 are related to vegetation moisture and C_3 represent the scattering component from the ground (soil moisture).

The parameter C_1 and C_2 and C_3 are obtained by non linear least square optimization method by using the minimizing problem

$$\sum_{i=1}^{N} \left\{\sigma^0_{i,obs} - \sigma^0_{i,mod}\left(Bm, C_1, C_2, C_3\right)\right\}^2 = \text{Minimize} \tag{5}$$

where, N is number of data $\sigma^\circ_{i,obs}$ is observed scattering coefficient data, $\sigma^\circ_{i,mod}\left(Bm, C_1, C_2, C_3\right)$ is modeled scattering coefficient for the best data.

Vegetation biomass (Bm) is then estimated from measured mean scattering coefficient and scaling factors C_1, C_2 and C_3 by solving (5) with respect to the vegetation biomass

$$Bm = \frac{1}{2C_1} \ln\left(\frac{\sigma^\circ + \frac{C_1}{2C_2}}{C_3 + \frac{C_1}{2C_2}}\right) \tag{6}$$

3.4.2. Step 2: Extrapolation of the Data Obtained from Step 1

The obtained data is extrapolated using polyfit function (fitting a polynomial) of MATLAB so that we have sufficient number of data for training, testing and validating the multi-layer ANN model.

3.4.3. Step 3: Development of Multilayer Neural Network, Its Training and Testing

A multilayer neural network is created [2, 3] and back propagation algorithm is used for training and testing of network with the relationship developed in Step 1.

These are the pre requisite modeling and approach for retrieval of vegetation parameters (i.e., SM, Bm).

Now, the process used in training, testing and validation of neural network is as discussed in the flowchart (Figure 5). The algorithm given in the flowchart 5 is the broad steps that have been taken for retrieving the parameters.

The procedure is structured into several steps as shown in the flowchart given in Figure 5. First of all different lady finger fields for which detailed ground truth were available are used to test the model. Then the model uses the same ground data (reference) as input and generates a set of outputs. Thereafter, using retrieved parameters,

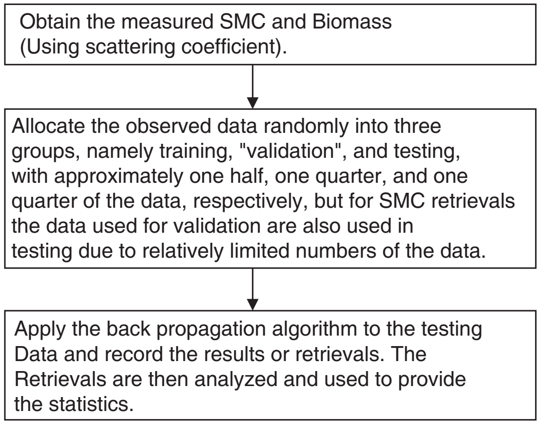

Figure 5. Flow chart for process used in training, testing and validation of neural network.

estimate the difference between the crop cycle of the reference site and the crop cycle of the test site and hence, the time evolution of its vegetation variables. Finally the results are compared with ground truth measured at the test site.

The algorithm involves some assumptions. However, it has the advantage of fully exploiting the potential of training the network with model outputs that consider the evolution of all vegetation variables.

3.5. Implementation of Retrieval Algorithm

As far as first step is concerned, the field analysis has been carried out as written in Sections 3.1 to 3.3. It is observed that VV-polarization is giving better values of R^2 than HH-polarization which indicates that for further retrieval analysis we have to use the VV-polarization data. In VV-polarization also angle 55 degree is giving the best R^2 value (Table 5) for composite effect of Bm and SM on scattering coefficient of ladyfinger. Therefore for development of retrieval algorithm with neural network, we have used VV-polarization with incidence angle 55 degree.

Second step is done by training the multilayer neural network through the data of reference field (Table 2 and methods discussed in Sections 3.4.1 and 3.4.2).

Third step is little bit complex but more advance approach is based on the combination of neural network with vegetation and soil models.

Neural network establishes the inverse mapping and the input output discriminate relations during the training phase on the basis of data generated by electromagnetic model and soil vegetation models (Section 3.4.1) [2, 3]. Finally time shifting is done to retrieve the parameters of different field from the same network.

As stated earlier, several soil and vegetation variables influence the scattering coefficient. A procedure based on a full inversion of all variables would be too difficult. The retrieval procedure used in this paper however, does not lead to any numerical complexity.

This section describes two approaches based on neural networks trained by the model illustrated in the previous section. The topology is formed by multilayer perceptron with hidden layers.

3.5.1. General Aspects of Retrieval Process

A reference field for which a complete set of detailed ground data corresponding to different "day of year" (Doy) is available, has been selected for training the neural network (Table 2). Data has been collected for different scatterometer configuration and has been extrapolated to make large amount of samples to train the network.

3.5.2. Soil Moisture Retrieval

First of all soil moisture has been retrieved. A neural network is created and trained with the available set of data. In the training phase, the input-output pairs of the σ_c° and soil moisture are used. In the test phase, the soil moisture values corresponding to the dates of the scatterometer measurements at the test sites are considered as unknowns to be retrieved (as mentioned in Section 3.4.1).

A set of measured σ_c° is fed to the trained network, giving the estimated soil moisture as outputs. The estimated values of soil moisture are in good agreement with the measured values of soil moisture. This retrieval is performed by same network with different set of data as mentioned by Fabio Del Frate et al. [2, 3].

But this was used only for SM retrieval while we can find the vegetation parameter i.e., Bm using empirical relations as stated in Eq. (6).

3.5.3. Vegetation Variables (Parameters) Retrieval

Now using the same network for the retrieval of vegetation parameter of second field, it is obvious that the results will be erroneous. Hence there is a need of developing time evolution relation between the two fields.

The basic concept of the retrieval procedure is to assume that other fields of the same crop/vegetation type will have a similar growth cycle, but shifted in time. That is, if $(\mathrm{Doy})_r$ represents the trend of a vegetation variable throughout the reference field i.e., crop/vegetation cycle, it has been assumed that the same cycle will hold true for a crop/vegetation variable $[(\mathrm{Doy})_d]$ of a different field of the same crop/vegetation.

It is given as

$$[(\mathrm{Doy})_d] = Z_v[(\mathrm{Doy})_r] \tag{7}$$

where Z_v is a constant factor for crop/vegetation variable. The correspondence between the generic day at different field $(\mathrm{Doy})_d$ and the $(\mathrm{Doy})_r$, at reference site is given by

$$(\mathrm{Doy})_r = x^*(\mathrm{Doy})_d + Y$$

In the above expression, x is a factor which modifies the width of the time trend, while Y is the parameter which modifies the time location of the cycle.

Now, using this $(\mathrm{Doy})_r$ and scattering coefficient of the data of second field a network has been trained and made to minimize the error of retrieval (Figure 6) as given in Eqs. (8) and (9).

$$Z_1^*(\mathrm{SM}') = \mathrm{SM}(\exp) \tag{8}$$

$$Z_2^*(\mathrm{Bm}') = \mathrm{Bm}(\exp) \tag{9}$$

Where SM' is retrieved value of soil moisture at particular time and SM(exp) is the observed value at the field. Similarly Bm is retrieved value of biomass at particular time and Bm(exp) is the observed value of biomass at the field. Z_1 and Z_2 are the error minimization factor. Here, Data of field 2 is used to minimize the error and corresponding value of x, Y, Z (range of values) has been found for minimum error.

The network has been simulated number of times by varying the values of x, Y, Z and then values has been defined for which error is minimum. After the training and error minimization, the procedure is tested at test site data. A multi temporal set of σ_c° has been measured at the same frequencies, polarization and angles as those of training phase is taken for validation.

As far as vegetation parameters are considered, using experimental σ_c° as input, the network estimates the differences between the ground data for the test field and those for the reference field. Further time evolution is done. The outputs provided by the network are the variables x, Y, Z containing information about the temporal evolution of the test cycle. These variables are calculated using the procedure and equations indicated in Eqs. (7), (8), and (9). In this way, all vegetation variables may be estimated for the whole test cycle.

3.6. Specific Issues

The retrieval algorithm used here may be a complete solution of the retrieval problem. In the model, it is assumed that scattering coefficient is affected by soil moisture and biomass only. A direct approach of inverting the relation by solving equations would be difficult because unknowns are much more than the number of equation that will be formed. Moreover, methods based on simple one to one relationship between σ_c° and single vegetation parameters are heavily influenced by the specific properties (like variance, mean, type of distribution) of the data set.

The effect of dataset is also there on the used algorithm. Like if the network would have been trained with large number of data set then the output results will be more optimized. In the network training phase, the model was trained for every set of interpolated data. Also to generate the time evolution coefficients we varied the value of variables till optimization is achieved.

3.7. Retrieval Results

The method explained in the paper is used on the dataset to obtain the results. We have used the data of scattering coefficient for VV-pol at 55 degree incidence angle. There was very few samples of data hence we interpolated it for all days to have a large number of samples.

The network used has 2 layers only with 10 nodes in 1st layer and 2 nodes in 2nd layer as the output variables are 2 (Figure 6).

By soil moisture retrieval method, we got results which are not good enough, as the trained network is heavily affected by the dataset. We trained the network with few of the data of the 1st field and estimated SM by the network for the same field then we got very good results (Figure 7) but in the case when we trained the network using

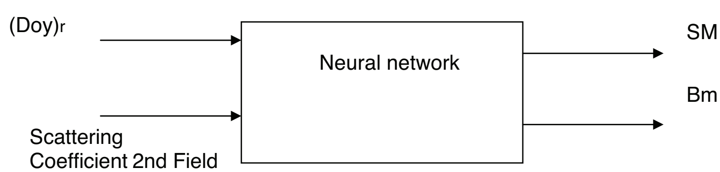

Figure 6. Flowchart for training the Neural Network.

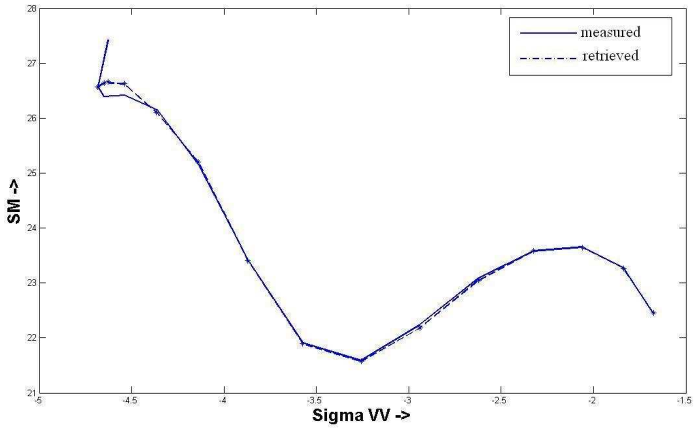

Figure 7. SM retrieved by training the network for the same field (1st).

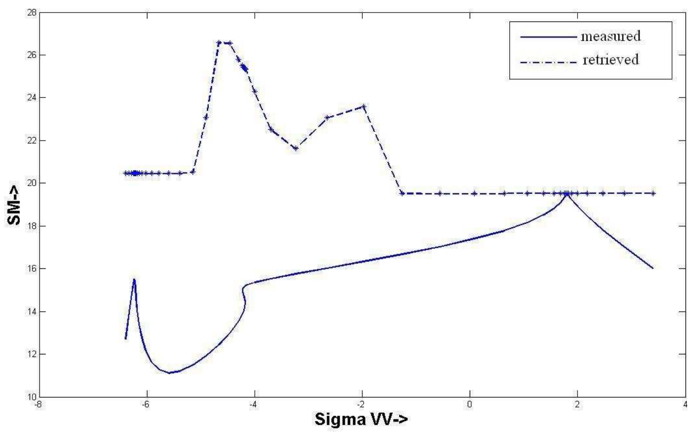

Figure 8. SM retrieved for 2nd field when network trained using 1st field.

data of 1st field and then used it to retrieve SM for 2nd field (Figure 8) the result was erroneous.

Hence time evolution has been applied i.e., 2nd method in which other parameters have been also used. It gave very good results.

Varying the values $x = 0.1$ to 2 and $Y = -50$ to 50 and $Z = 0.1$

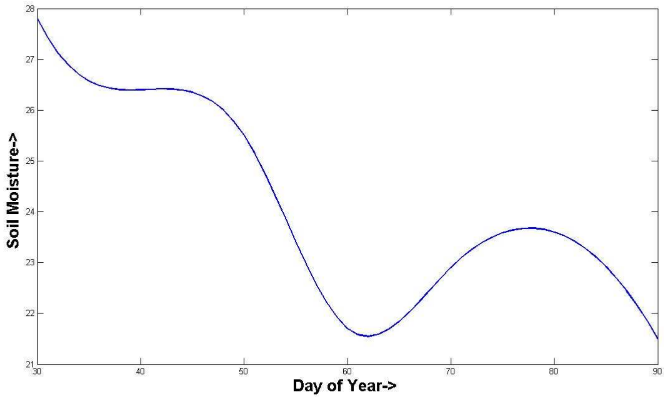

Figure 9. SM of reference field with days.

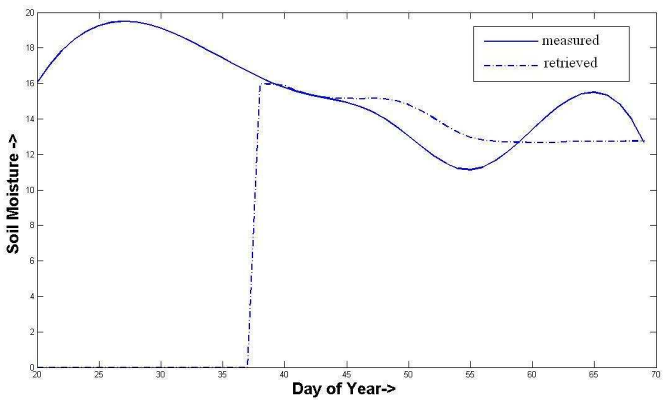

Figure 10. Retrieved soil moisture of second field with days.

to 2. We optimized the network for different combinations of above x, Y, Z values and got the best results for the case

When $x = 0.12$, $Y = 25$, $Z_1 = 0.56$, $Z_2 = 1.22$.

It means that the $(\text{Doy})_r$ is obtained by scaling time i.e., Doy by a factor of 0.12 and then time shifting by 25 Days. These values of $(\text{Doy})_r$ and corresponding values of scattering coefficient are then fed into the network and obtained SM′ and BM′ for that particular Doy and finally these are scaled by a factor of 0.56 and 1.22 respectively to get SM and BM i.e., retrieved SM and BM. Retrieval results for soil moisture and biomass of reference field and other field are shown in Figures 9–12.

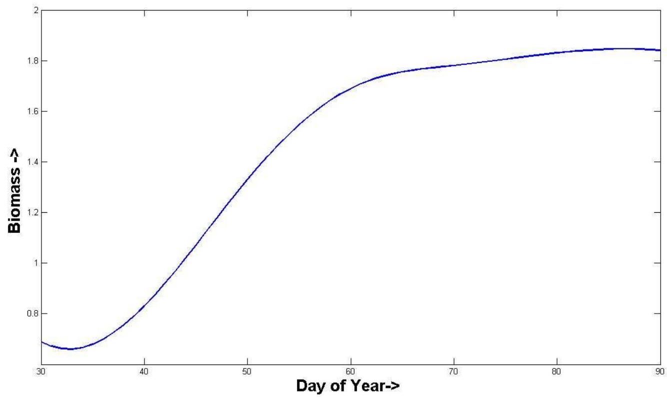

Figure 11. Biomass of reference field.

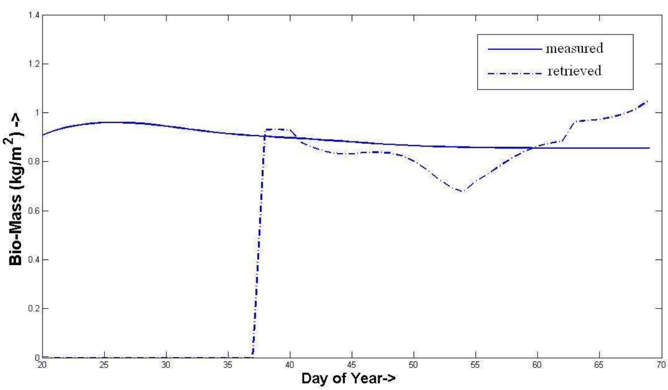

Figure 12. Retrieved biomass of second field.

The final SM and Bm values thus obtained are then compared to the experimental data at that Doy and then error is calculated. For these the overall error came out to be 4.09% which is quite good considering the fact that we had very few data with us and the 2 fields taken were very different from each other this can easily be seen from the value of x, as it came out to be too low which tells that the 2 fields differ from each other a lot. This error can further be reduced by taking the data from many fields and by using the data of related fields.

Error in biomass retrieval is little more as compared to SM. We performed the mapping through the network, so few of the values had fallen out of range of 1st field so in starting from day 20 to day 37 all values were taken zero to show that it went out of the networks region. This error can also be removed by using data from more fields.

4. CONCLUSIONS

An efficient algorithm has been used for retrieving various vegetation parameters (soil moisture, and biomass) with the time evolution of the properties of "Ladyfinger" crop that is based on the scattering coefficient and neural networks. The algorithm takes the time evolution for vegetation variables into account, giving a method which is very fast and efficient to retrieve various vegetation parameters.

The accuracy of the result is fair when time evolution is performed for the test field. In future the retrieval procedure can be improved by also using different band and radar configuration and also planning the schedule in such a way that the reference field and field to be monitored may have same general properties i.e. the data sets are more correlated.

This research is aimed to propose an efficient and general algorithm for retrieval of vegetation parameter with radar scattering, while more accuracy can be brought in through further research and modification.

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Erratum to APPLICATION OF NEURAL NETWORK WITH ERROR CORRELATION AND TIME EVOLUTION FOR RETRIEVAL OF SOIL MOISTURE AND OTHER VEGETATION VARIABLES by D. Singh, V. Srivastava, B. Pandey, and D. Bhimsaria, in *Progress In Electromagnetics Research B*, Vol. 15, pp. 245–265, 2009

1. Table 2 of page 250 should be replaced by following table

Table 2. Field parameters of ladyfinger (reference field).

AGE	Biomass(kg m^{-2})	SM
20	0.58	16.3
30	0.66	27.8
34	0.62	26.7
41	0.81	26.2
48	1.21	26.1
55	1.61	23.5
62	1.68	21.3
69	1.75	22.5
75	1.82	23.2
82	1.82	22.8
90	1.83	21.7

* Biomass - Bm, SM - percentage of soil moisture (gravimetric)

2. **Page 250**, **Line 3–5**: "The observations of ladyfinger were taken every ten days of interval up to 90 days of sowing." This should be replaced by "The observations of ladyfinger were taken every seven to ten days of interval up to 90 days of sowing."