ESTIMATING THE SOIL MOISTURE CONTENT VIA SCATTERING MEASUREMENTS ALONG THE SPECULAR DIRECTION AT L-BAND USING NEURO-FUZZY INFERENCE SYSTEM

6.1 INTRODUCTION

Soil moisture contents play a crucial role in controlling the agricultural parameters, land surface water, environment, climate change, etc. of our earth and atmosphere. Soil moisture of land surface influences the dynamics of the atmospheric boundary layer, which directly affects the climate (Engman 1991, Engman and Chauhan 1995). Nowadays, several remote sensing techniques are being used to measure soil moisture of land surfaces. The air-borne and space-borne remote sensing techniques based on gamma radiation, infrared spectrometers, and active and passive radar systems have proved their potential for soil moisture estimations with promising accuracy. Out of active radar systems, microwave remote sensing has promising approaches for assessing the soil moisture content of land surfaces. Since it has higher sensitivity towards dielectric and geometric properties of the land surface object and its higher capability of penetration into the objects. Moreover, the microwave has the potential to obtain the land surface observation at different band independently (Ulaby et al. 1982).

The studies of the microwave scattering of natural land surfaces were studied, and their relationships with moisture contents and roughness have been reported in the different literature (Oh et al. 1992; De Roo et al. 1994; Mattia et al. 1997; Wagner 1998; Yang et al. 2000). The experimental study using ground-based, air-borne, and space-borne sensors for retrieving the surface soil moisture content and surface roughness parameters have shown the high potential of microwave bands (Shi et al. 1997; Yang et al. 2000; Baghdadi et al. 2006;

Khadhra et al. 2012). Oh et al. (1992) and Dubois et al. (1995) established the semi-empirical models between the microwave scattering coefficients and soil surface parameters, i.e., soil moisture content and roughness parameters. However, these semi-empirical models have limitations because of the range of validity for surface roughness and soil moisture content in a single modeling approach, and these models do not represent for a large range of surface roughness and soil moisture content. Many studies in the literature have been described for the estimation of the soil moisture content and surface roughness parameters using microwave remote sensing data. But the literature lacks how to separate soil moisture content and roughness parameters for accurate estimation using single remote sensing data. Since the developed models are complex and have lots of land surface parameters, this causes limitations on the use of complex existing models. Therefore, researchers have started to use the polarimetric behaviour of microwave radar data incorporating the information of orientation and shape of the targets and simplifying the retrieval algorithm for soil moisture (Ulaby et al. 1982; De Roo et al. 1994; Ceraldi et al. 2005).

Till now, very few reported works on polarimetric bistatic radar data are available for retrieval of soil moisture. At present, the bistatic satellite programme is becoming more interesting where one satellite is transmitting, and different combinations of bistatic receivers will be used for specific scientific purposes for different targets. Therefore, there is a need of bistatic experimental study for complex objects and design a less complex mathematical model for their parameter retrieval. At the present time, mostly active microwave remote sensors (i.e., Synthetic aperture radars, Altimeters, and Scatterometer mounted on the European remote sensing satellite, Envisat, Radarsat, Japanese Earth resources satellite, Risat1-2) are monostatic satellite which measures scattered signal only in the back direction. However, bistatic configurations of the radar system are being considered by the scientific community to broaden the information of land surface observations. For example, ground-based receivers can be used as a bistatic radar that may collect scattered signal for the target on land surfaces transmitted by a satellite. Currently, bistatic remote sensing configurations from TanDEM-X with two TerraSAR-X satellites kept in closed formation have been recently placed in the space (Rodriguez-Cassola et al. 2012). Therefore, to extend the knowledge about bistatic configurations, the polarization behaviour of the microwave scattering were used to retrieve the soil moisture content at a constant value of surface roughness.

The scattering mechanisms of the microwave with the natural soil surfaces are complex. Their mathematical modeling involves very complicated expressions with natural soil surface parameters. For the last decade, many useful modeling approaches on nonparametric algorithms, such as an artificial neural network (ANN), support vector regression (SVR), and fuzzy logic (FL), etc. have been studied for the estimation of biophysical/geophysical parameters on the land surfaces. These non-parametric models provided reasonable results for their estimation. The machine learning algorithm is a model free estimator, and it maps the nonlinear input-output data through a process called training of the data sets. Many researchers (Chang and Islam 2000; Del Frate et al. 2003; Jiang and Cotton 2004; Chai et al. 2009; Dharanibai and Alex 2009; Ahemad et al. 2010) have used machine learning algorithm for the estimation of soil moisture content. However, the estimation of soil moisture content are yet to be reported in the literature using the bistatic scatterometer data by a hybrid machine learning algorithm called the neuro-fuzzy inference system (ANFIS).

Therefore, for the above purpose to be fulfilled, the objective of this study was to obtain the suitable and reliable data using microwave bistatic scatterometer data at L-band for HH-and VV-polarization for various incidence angles and to develop the neuro-fuzzy algorithm for the estimation of soil moisture. To reduce the number of parameters to be estimated, it is possible to combine scattering measurements at different polarizations in order to cancel out the dependence on surface roughness. Hence, the ratio of scattering coefficients at HH- and VV-polarizations was proposed for soil moisture estimation along the specular direction for different incidence angles at L-band. The ratio of scattering coefficients at HH- and VV-polarizations is called the co-polarization ratio $P(P = \frac{\sigma^{\circ}_{HH}}{\sigma^{\circ}_{VV}})$. Its evaluation using the ratio of scattering coefficients is rather robust as compared to single scattering coefficients at HH- and VV-polarizations, applicable for larger surface roughness values. The grid partition based neuro-fuzzy inference system (G-ANFIS) was used for the soil moisture estimation using P value. The performances of three memberships function (MF) such as generalized bell (gbell), Gaussian (Gauss), and triangular (tri) were investigated for the soil moisture estimation.

6.2 EXPERIMENTAL DETAILS

The bistatic specular scatterometer measurement was performed over specially prepared outdoor test bed of bare soil surface of area 10 m × 10 m beside the Department of Physics, Indian Institute Technology (B.H.U), Varanasi, India. The L-band bistatic scatterometer observations were taken for five values of soil moisture contents of bare soil surfaces for the angular range 20°- 60° in steps of 10° at HH- and VV- polarizations. The specifications of the bistatic scatterometer set-up employed for the outdoor bistatic measurements at the different moisture content of slightly rough bare soil surface are given in Table 2.1 and the detailed procedure for the bistatic scatterometer measurements and soil surface parameters measurements are described in Chapter 2. During the microwave response of soil moisture measurement, the surface roughness was kept constant. The soil roughness, such as root mean square (RMS) height (*s*) and correlation length (*l*) was found to be 2.15 cm and 9.62 cm, respectively, under the study of test bed of bare soil surface. The measured gravimetric soil moisture content was 11.55%, 17.14%, 21.28%, 25.40%, and 31.12%. The percentages of soil texture constituents have the values 52.96%, 27.14%, and 19.88% for sand, silt, and clay, respectively, for the soil under study.

6.3 METHODS

6.3.1 G-ANFIS

The ANFIS based on grid partition is called the G-ANFIS. In this method, the input data are partitioned into regions that are predefined by membership function using axis parallel partition called grid (Abonyi et al. 1999). Each of these grids generates the fuzzy rules in the input-output data of the system. The performance of FIS based on grid partition depends on the number of the grids. For the finer grid, the performance of fuzzy FIS is better, but due to the increase in the numbers of the grid, the number of fuzzy rules associated with the FIS increases exponentially.

For the estimation of soil moisture using G-ANFIS, the three membership functions (MF), namely Gaussian (Gauss), generalized bell (gbell), and triangular (tri) MF and their optimum number of membership function were investigated for partitioning the input data sets. These MF are defined as

(i) Gaussian membership function (Gauss MF)

$$\mu(x, a, b) = e^{\frac{-(x-b)^2}{2a^2}}$$

Where *b* and *a* represent the center and width of the Gauss MF.

(ii) Generalized bell membership function (gbell MF)

$$\mu(x, a, b, c) = \frac{1}{1 + \left|\frac{x - c}{a}\right|^{2b}}$$

Where the parameters *c* determines the center of the function, *a* is half-width and *b*, together with *a*, controls the slopes at crossover points.

(iii) Triangular membership function (tri MF)

$$\mu(x,a,b,c) = \begin{cases} 0\ , & x \le a \\ \dfrac{x-b}{b-a}\ , & a \le x \le b \\ \dfrac{c-x}{c-b}\ , & \mathrm{b} \le x \le c \\ 0, & \mathrm{c} \le x \end{cases}$$

The parameters (*a, b, c*) with *a* >*b* > *c* determines the three corners of the tri MF.

The basic structure of the G-ANFIS algorithm and its description are the same as the S-ANFIS algorithm described in Chapter 5 for one input, and one output data sets for the two rules, i.e., K=2 with the only difference in their MF. In the present study, the ***genfis1*** and ***anfis*** functions of the fuzzy logic toolbox available in the MATLAB was used to develop the G-ANFIS algorithm for the estimation of soil moisture content using the co-polarization ratio *P*.

6.4 RESULTS AND DISCUSSION

6.4.1 Angular variation of scattering coefficients and co-polarization ratio *P* (dB) for different soil moisture contents

Figures 6.1 and 6.2 show the angular variation of bistatic specular scattering coefficients ($\sigma°$) at five gravimetric soil moisture content (11.55%, 17.14%, 21.28%, 25.40%, and 31.12%) for bare soil surface at L-band for HH- and VV-polarizations. The bistatic scatterometer measurements were taken at the same value of surface roughness parameters during the entire observations. The $\sigma°$ depends upon the soil properties such as dielectric constant, roughness parameters, and chemical composition and system parameters like incidence angle, polarization, and frequency of scatterometer. The values of $\sigma°$ were found to increase with the soil moisture content at HH- and VV-polarizations. Since, as the soil moisture content increases, the values of dielectric constant increase. Therefore, there is an increase in the value of reflectivity from the soil surface of the incident microwave radiation in the specular direction which led to increase in the values of $\sigma°$ with the soil moisture content for both polarizations (Dobson and Ulaby 1981; Ulaby et al. 1982; Bertuzzi et al. 1992; Khadhra et al. 2012). According to Fresnel's equation for reflection, the reflectivity at HH-polarization increases with the incidence angle in the specular direction. However, at VV- polarization, the reflectivity decreases until the Brewster angle of incidence is reached, and after that, it started to increase again. Therefore, $\sigma°$ was found to increase with the incidence angle at HH-polarization and decrease at VV- polarization up to 50° angle of incidence. After then, it started increasing again. Since, in between the 50° and 60° angle of incidence, due to Brewster angle of incidence, the reflectivity is minimum, after Brewster angle of incidence, the reflectivity started increasing again; therefore, the $\sigma°$ at VV-polarization started increasing again. Thus, the difference between the levels of $\sigma°$ at HH- and VV-polarization decreases after 50° angle of incidence. In addition, from Figures 6.1 and 6.2, it is observed that the separation between the value of $\sigma°$ with soil moisture increases as the soil moisture decrease for almost all the angle of incidence. This behaviour of $\sigma°$ is attributed to increase in the penetration depth with the decrease in the soil moisture content, and hence, there is a rapid decrease in the reflected components at the lower value of the soil moisture content as compared to the higher value of soil moisture content. Therefore, the separation between $\sigma°$ values increases with the decrease in the soil moisture content for almost all the angles of incidence.

Now, the observed scattering coefficient at HH- and VV-polarization was used to calculate the co-polarization ratio $P = \frac{\sigma^{\circ}_{HH}}{\sigma^{\circ}_{VV}}$ at different incidence angle for five soil moisture content. Since the computed scattering coefficients are in dB, therefore, the differences of the scattering coefficients at HH- and VV-polarizations were taken to calculate the co-polarization P in dB i.e.

$$P\,(\text{dB}) = \sigma^{\circ}_{HH}\,(\text{dB}) - \sigma^{\circ}_{VV}\,(\text{dB})$$

Figure 6.3 shows the angular variation of the calculated *P* (dB) values for five soil moisture content. It is observed that *P* (dB) values increase with the angle of incidence as well as with soil moisture content. The dynamic range of *P* (dB) values from the highest value of soil moisture content to the lowest value of soil moisture content increases with the angle of incidence from 30° to 50°. However, the dynamic range at 20° was found slightly higher than at 30°. After 50° angle of incidence, the dynamic range was found to decrease again.

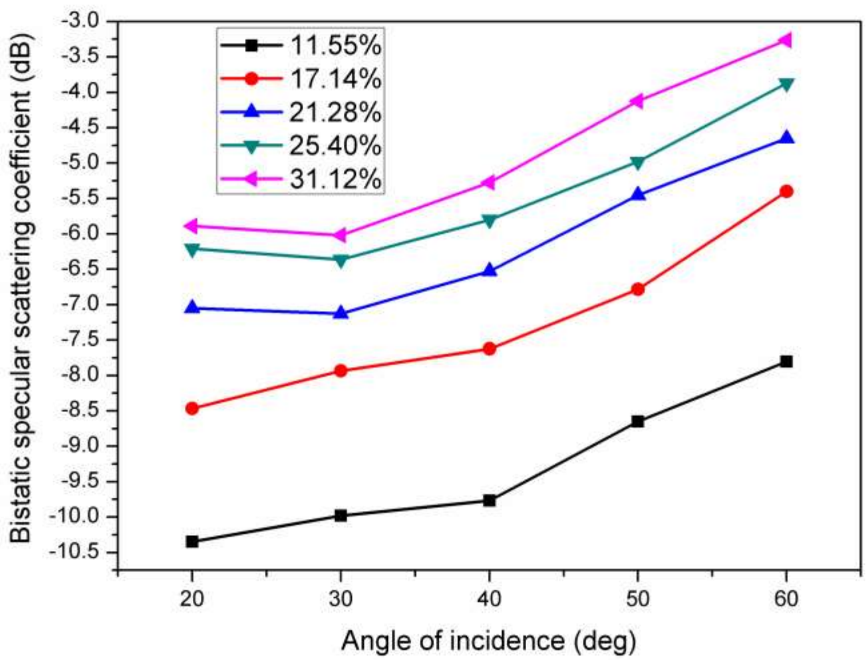


Figure 6.1 Angular variation of scattering coefficients at different soil moisture for HH-polarization at L-band

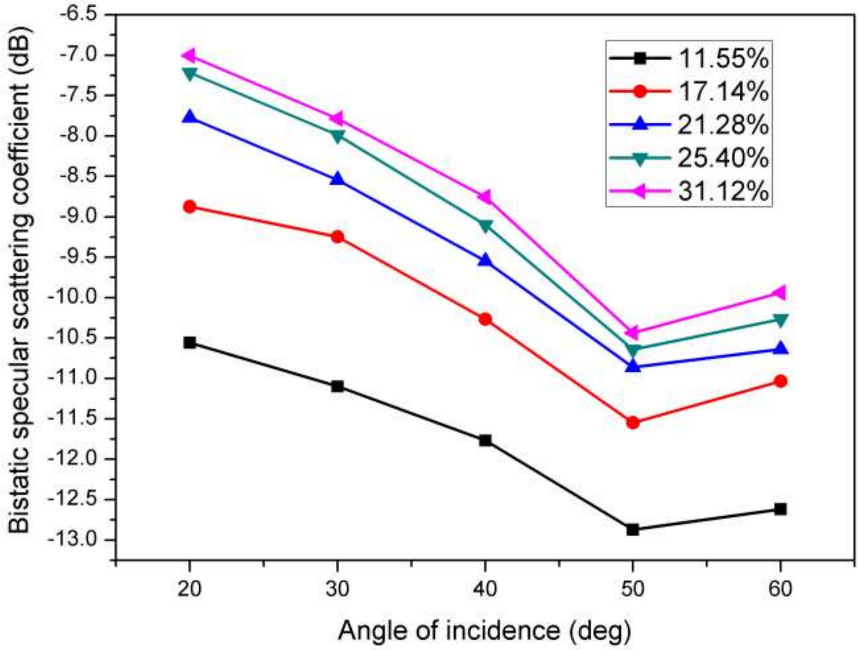


Figure 6.2 Angular variation of scattering coefficient at different soil moisture for VV-polarization at L-band

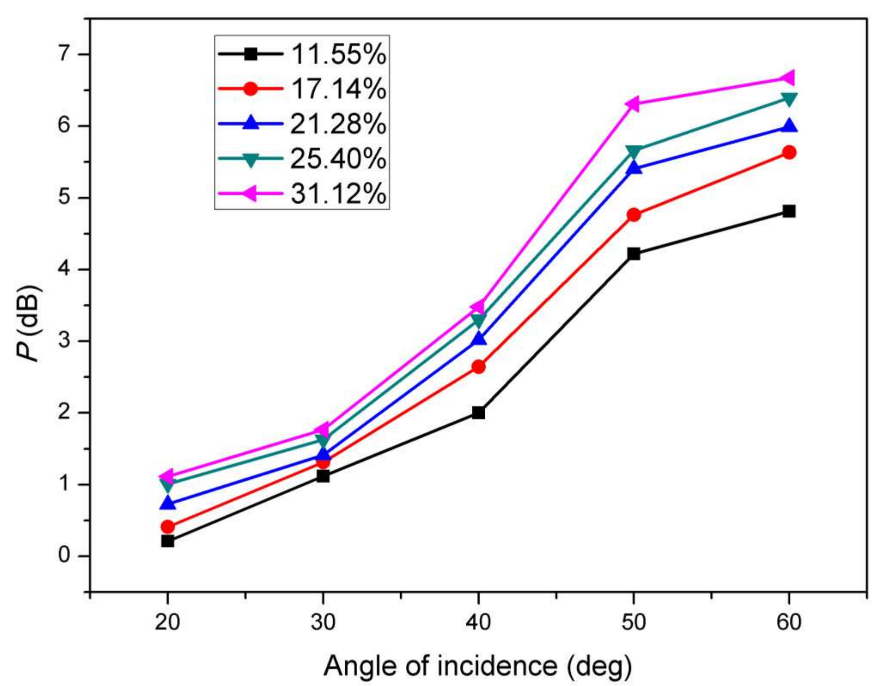


Figure 6.3 Angular variation of *P* (dB) at different soil moisture content

6.4.2 Evaluation of data sets

Table 6.1 shows the correlation results between the co-polarization ratio *P* (dB) and soil moisture content at incidence angle ranging from 20°-60° at steps of 10°. The correlation analysis was used for the evaluation of data and the selection of optimum incidence angle for the estimation of soil moisture using *P* (dB) values. The values of coefficients of determination (R^2) were found high at higher incidence angles as compared to lower incidence angles. Therefore, the *P* (dB) is more sensitive to the soil moisture content at higher incidence angles as compared to lower incidence angles. The high value of R^2 (0.970) was found at 50° angle of incidence. Therefore, the value of *P* at 50° incidence angle was taken for the estimation of soil moisture content by the nonparametric algorithm (G-ANFIS). The data sets at 50° incidence angle were interpolated to generate additional 60 data sets for training and testing of the G-ANFIS algorithm. These 60 data sets were classified into training and testing data sets. Out of these 60 data sets, every 4th data set was chosen for testing, and the remaining data set was taken for the training of G-ANFIS. The value of *P* (dB) and soil moisture content was taken as input and output data, respectively, for the training of the G-ANFIS algorithm.

Table 6.1 Coefficient of determination (R^2) between *P* (dB) and soil moisture content at different angle of incidence

Angle of incidence (deg)	Coefficient of determination (R^2)
20	0.939
30	0.958
40	0.963
50	0.970
60	0.939

6. 4.3 Estimation of soil moisture content using three different MF for G-ANFIS

Three MF, namely Gauss, gbell and tri, and their optimum number were used for partitioning the co-polarization *P* (dB) data into grids to generate the number of rules between the *P* (dB) and soil moisture content for developing G-ANFIS algorithm. Three different MF based G-ANFIS algorithm was trained for the estimation of soil moisture content using co-polarization ratio *P* (dB). The details of training and testing data sets (*P* (dB) and soil moisture) for the training and testing of the G-ANFIS algorithm are given in Section 6.4.2. The number of MF for the G-ANFIS algorithm needs to be optimized for accurate results. During the training of the G-ANFIS, the performance of the G-ANFIS algorithm was evaluated at different numbers of MF using the trial-error method. The optimum number for the three MF was chosen by training the algorithm using a different number of MF from 2 at the steps of 1 by the trial-error method and observing the desired RMSE values between observed and estimated values at different number of MF (Chung et al. 2007). The optimum number of MF was chosen where RMSE values for the training and testing data started to diverge. Table 6.2 summarizes the RMSE values between the estimated and observed soil moisture content for the optimized number of three MF and various other parameters of the G-ANFIS algorithm. The optimum number of MF was found to be 6 for all three types of MF. Figures 6.4-6.6 show the MF plot for the tri, Gauss, and gbell with the *P* (dB), respectively. Figures 6.7-6.9 depict the plots between experimentally observed and estimated soil moisture for the tri, gauss, and gbell MF, respectively, during the training and testing of the G-ANFIS algorithm. During the testing of the algorithm, it was found that the gbell MF has the least RMSE value for the estimation of soil moisture content followed by Gauss and tri MF. Therefore, the estimation of soil moisture using gbell MF based G-ANFIS algorithm would be a better choice as compared to Gauss and tri MF by the co-polarization ratio *P* (dB).

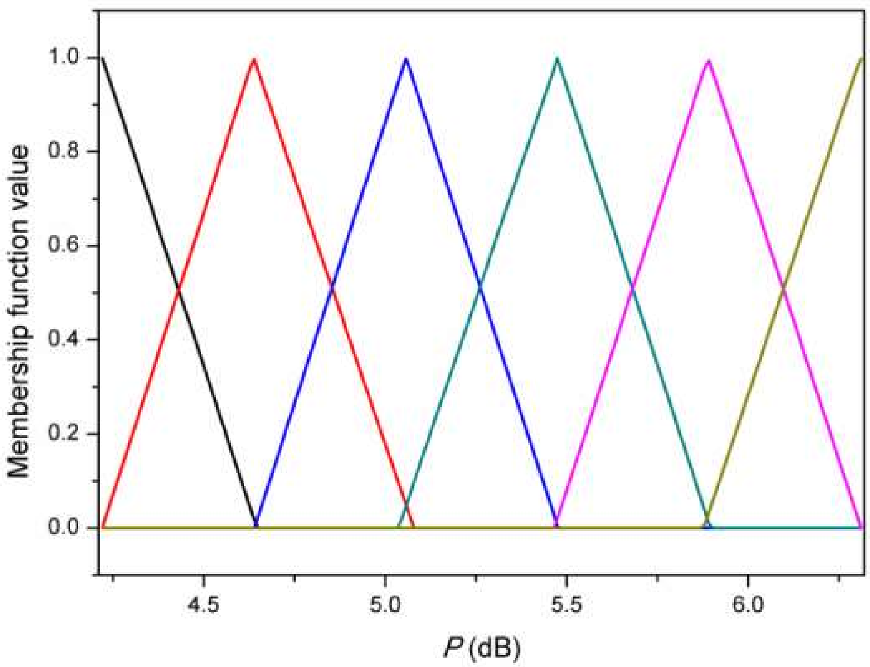


Figure 6.4 Membership function plot for tri MF with *P* (dB)

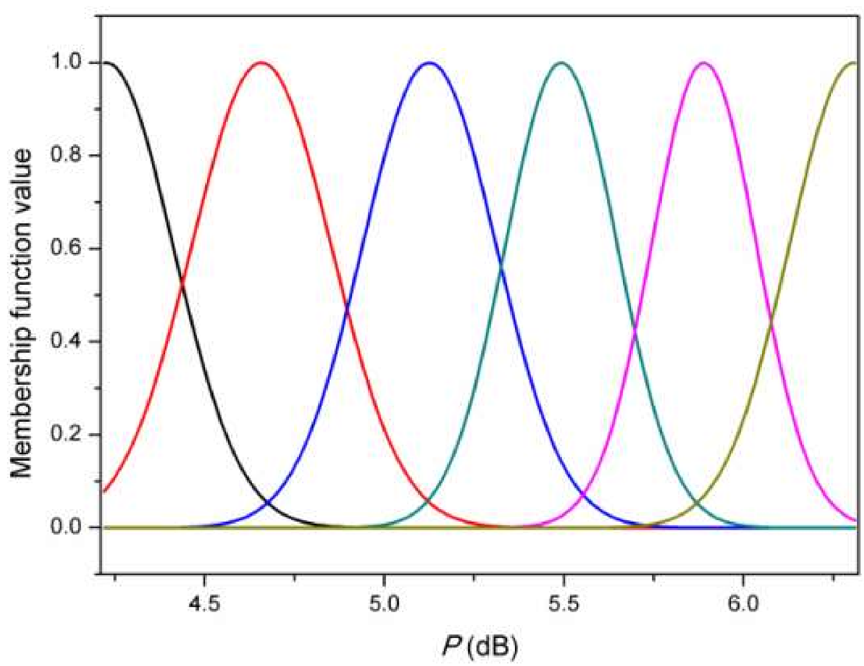


Figure 6.5 Membership function plot for Gauss MF with *P* (dB)

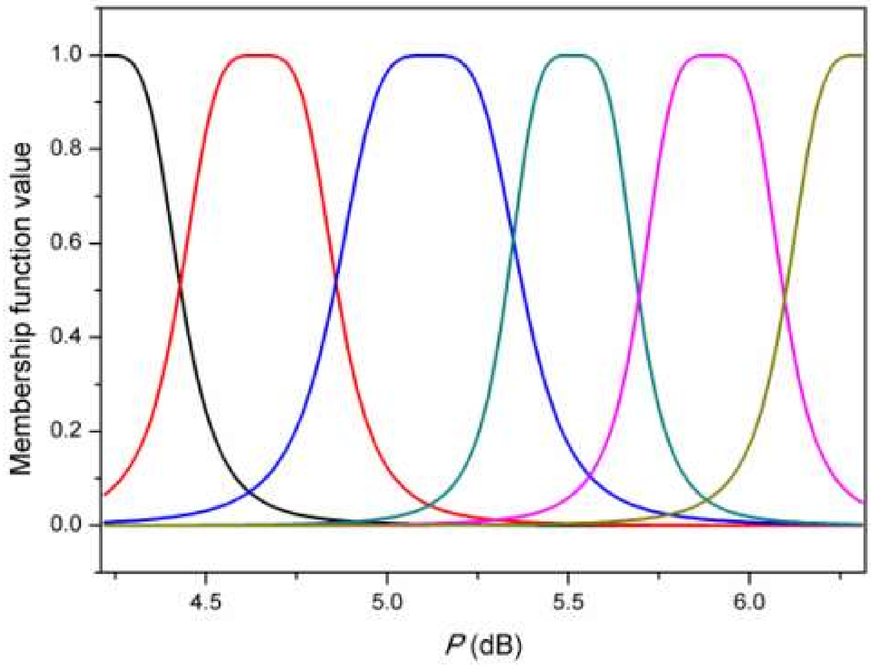


Figure 6.6 Membership function plot for gbell MF with *P* (dB)

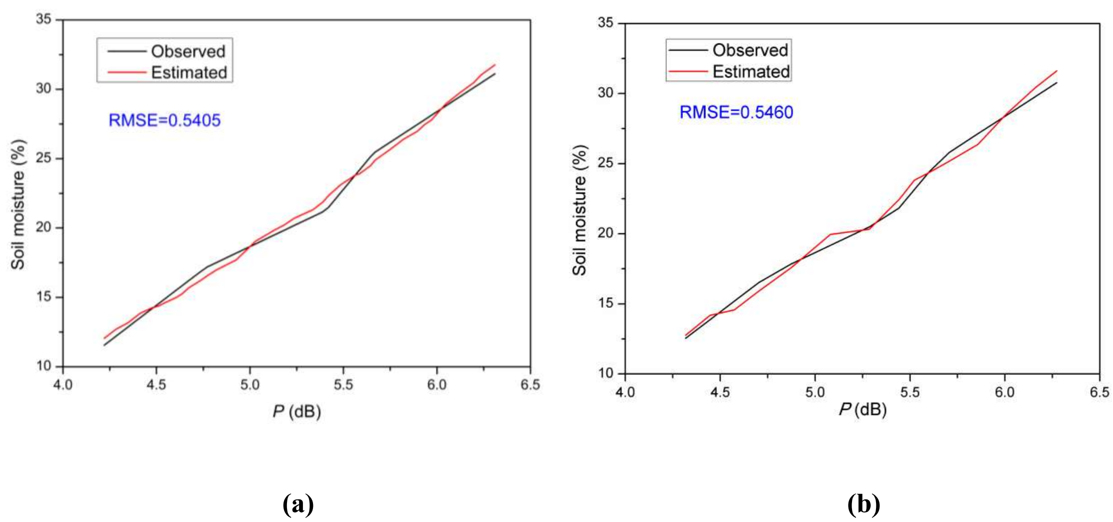
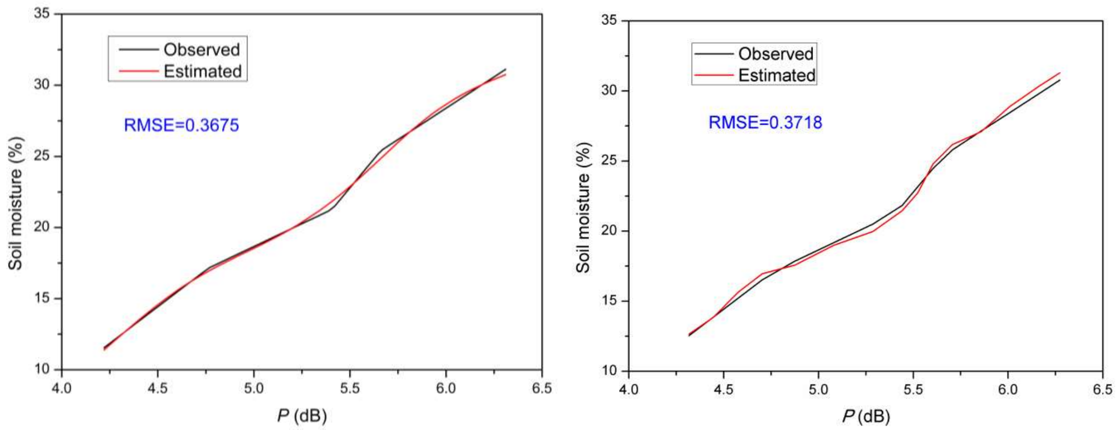
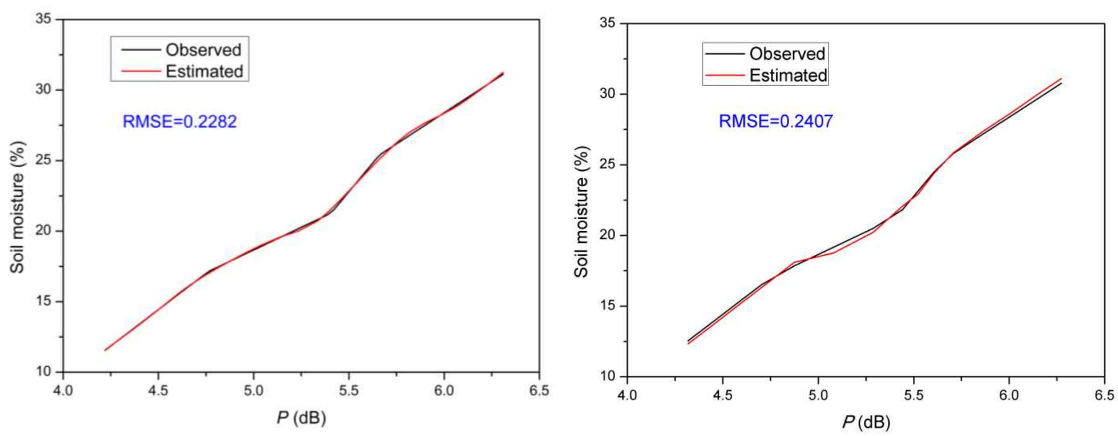


Figure 6.7 Plot between experimentally observed and estimated soil moisture for tri MF during (a) training and (b) testing of G-ANFIS algorithm



(a) **(b)**

Figure 6.8 Plot between experimentally observed and estimated soil moisture for Gauss MF during (a) training and (b) testing of G-ANFIS algorithm



(a) **(b)**

Figure 6.9 Plot between experimentally observed and estimated soil moisture for gbell MF during (a) training and (b) testing of G-ANFIS algorithm

Table 6.2 The optimum values of various parameters of G-ANFIS algorithm

Fuzzy parameters	Membership function (MF)		
	Triangular	Gaussian	Generalized bell
Optimum number of MF	6	6	6
Number of fuzzy rules	6	6	6
Number of membership functions	6	6	6
RMSE (training)	0.5405	0.3675	0.2282
RMSE (testing	0.5460	0.3718	0.2407

6.5 CONCLUSIONS

The bistatic specular scattering coefficient ($\sigma°$) was found to increase with the soil moisture content. The co-polarization ratio P (dB) was found to increase with the soil moisture content as well as with the angle of incidence. The optimum incidence angle for the co-polarization P (dB) with the soil moisture content was found to be at 50° angle of incidence. All the three MF were found promising for the accurate estimation of soil moisture content using bistatic scatterometer data by P (dB). The gbell MF based G-ANFIS was found better estimator among the three MF, followed by Gauss and tri.