CHAPTER - 5

ESTIMATION OF CROP VARIABLES USING BISTATIC SCATTEROMETER DATA AND ARTIFICIAL NEURAL NETWORK TRAINED BY EMPIRICAL MODELS

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5.1 INTRODUCTION

The application of microwave remote sensing to study the earth resources is becoming more popular by using scatterometer(Augusteijn et al. 1995; Ceraldi et al. 2005; Toure et al. 1994a), airborne (Ferrazzoli et al. 1997; Fitzjohn et al. 1998; Hoogeboom 1983; Macelloni et al. 2001; Ross 2009) and space born (Carreiras et al. 2006; Chauhan 1997; Cramer et al. 2001; Le Toan et al. 1997) in the field of agriculture.

One of the most important applications of microwave remote sensing is to monitor the crop/vegetation by investigating the scattering mechanism of microwave with the crop variables and their estimation at several growth stages. The phenomenon of scattering mechanism between vegetation constituents and the microwave is very complex for the analysis in the remote sensing. Inoue et al. (2014) have investigated the microwave backscattering response of leaf area index and biomass for the entire growth period of paddy crop at five frequencies (Ka, Ku, X, C, and L) for all polarizations (HH, VH, HV, and VV) in the angular range of incidence angles 25° to 55°. The backscattering coefficient is found enough sensitive to detect thin rice seedlings just after transplanting at higher frequency (Ka-, Ku-, and X-bands) and higher incidence angles**.** Taconet et al.(1998) investigated the radar backscattering of wheat field by an airborne scatterometer at C- and X-bands for both like polarizations (HH- and VV-). Both the underlying soil moisture and vegetation constituents at low frequency (C-band) attenuate the magnitude of backscattering coefficient. However, mostly the vegetation canopy influences the magnitude of backscattering coefficients at high frequency (X-band).

Various modeling approaches have been developed for better understanding of interactions of microwave signals with the vegetated and forest targets (Du et al. 2000; Wang and Qu 2009; Wood et al. 1992). Karam et al. (1995) has developed a scattering model for layered vegetation based on an iterative solution of the radiative transfer equation up to the second order to account for multiple scattering within the canopy and between the ground and the canopy. This model is designed to operate over a wide frequency range for both deciduous and coniferous forest parameter measurements with good results at both like and cross polarizations.

These microwave vegetation models are very difficult to solve inversion problem and understand the microwave response of individual crop variables for a particular crop. It requires large number of input data sets. Nowadays, several researchers have shown great interest towards artificial neural networks (ANN) as a model free tool in the field of remote sensing for the estimation of crop variables (Oh et al. 1992; Ulaby et al. 1981; Wilkinson et al. 1995). It is pursuit of worthy to combine an artificial neural network with appropriate vegetation electromagnetic models (physical, semi-empirical or empirical) for the estimation crop variables. Del Frate et al. (2003) have trained two artificial neural network algorithms by physical vegetation model for retrieving the soil moisture and vegetation variables of wheat crop.

In the present study, the observations were taken on specially prepared two parallel crop beds of kidney bean at an interval of three days. The first crop bed was considered as a reference field to develop empirical models. These developed empirical models were used to generate the training data sets consistent with age of kidney bean crop for the training of ANN model. Hence, the prior knowledge about the soil surface properties and vegetation status are not required for the training of artificial neural network used for the estimation of crop variables of kidney bean crop. The observed data set (bistatic scattering coefficients and kidney bean crop variables) of the second crop bed were used for the testing of ANN model.

The objectives of the present study were (i) to determine the suitable bistatic scatterometer configuration for the accurate estimation of Kidney bean crop variables (ii) to establish a reliable relationship between the bistatic scattering coefficient (σ^0) and kidney bean crop variables to generate large input data set by empirical models for the training of ANN and (iii) to solve the inversion problem for the estimation of crop variables.

5.2 METHOD AND OBSERVATIONS

Crop kidney bean is taken as the broad leaf crop. It attained maximum average height of 49± 2 cm in our crop bed during the entire observations. The maturity age of crop was found to be 97 ± 5 days after the date of sowing. Table 5.1 shows the observed values of crop variables and soil moisture of reference crop bed of kidney bean crop.

Table 5.1 The measured values of crop variables of kidney bean and soil moisture content during its entire growth period of the reference crop bed

Age (days)	Plant height (PH) (cm)	Vegetation water content (VWC) (Kg/m^2)	Leaf area index (LAI) (m^2/m^{-2})	SPAD value	SM (%)
26	11.2	0.18	0.17	27.8	22.17
39	18.7	0.21	0.84	30.6	22.03
47	25.3	0.53	1.54	33.8	23.20
54	32.5	0.63	1.93	36.5	20.41
63	39.8	1.05	2.27	41.0	19.36
75	44.5	1.53	2.63	42.6	18.07
91	47.4	1.93	2.83	38.9	19.82
97	49.2	1.98	2.76	35.0	22.56
104	49.0	1.86	2.48	27.3	20.80

5.3 STATISTICAL ANALYSIS

The linear regression analysis was done to understand the effect of individual crop variables of kidney bean on bistatic scattering coefficient at different incidence angle and like polarizations (HH- and VV-) at X- band. It was done also to find the suitable incidence angle of the bistatic scatterometer system to estimate the crop variables using multi-temporal, multi-angular and like-polarized bistatic scatterometer data. Table 5.2 shows the linear regression results between bistatic scattering coefficients and kidney bean crop variables at different combinations of bistatic scatterometer parameters.

5.4 MODELLING APPROACH

5.4.1 MULTIPLE REGRESSION ANALYSIS

The multiple regression analysis was done to analyze the composite effect of all the crop variables on bistatic scattering coefficients. Only three crop variables of kidney bean (VWC, LAI and PH) were considered for the multiple regression analysis. The fourth crop variable (SPAD value) was not considered due to its poor correlation observed with the bistatic scattering coefficient.

Table 5.2 Result of regression analysis between bistatic scattering coefficients and kidney bean crop variables at different incidence angles for HH- and VV- polarization

Crop variables ↓		HH-polarization						VV- polarization					
		Incidence angle						Incidence angle					
		20°	30°	40°	50°	60°	70°	20°	30°	40°	50°	60°	70°
VWC	R^2	0.88	0.89	0.90	0.91	0.83	0.81	0.86	0.90	0.91	0.92	0.91	0.86
	SE	0.23	0.23	0.23	0.24	0.22	0.22	0.23	0.24	0.24	0.24	0.24	0.23
	SEE	0.24	0.23	0.23	0.20	0.29	0.31	0.26	0.22	0.21	0.20	0.20	0.26
LAI	R^2	0.79	0.78	0.83	0.80	0.86	0.82	0.84	0.86	0.86	0.87	0.82	0.77
	SE	0.30	0.30	0.31	0.30	0.32	0.31	4.58	4.62	4.60	4.65	4.52	4.39
	SEE	0.44	0.45	0.40	0.43	0.35	0.41	3.70	2.64	2.77	2.12	3.70	4.80
PH	R^2	0.89	0.90	0.94	0.95	0.92	0.94	0.79	0.82	0.88	0.82	0.78	0.73
	SE	0.30	0.31	0.34	0.31	0.30	0.29	4.45	4.46	4.56	4.63	4.52	4.57
	SEE	0.44	0.41	0.35	0.41	0.45	0.50	4.36	4.25	3.33	2.92	3.76	3.23
SPAD value	R^2	0.13	0.16	0.18	0.22	0.14	0.18	0.17	0.22	0.26	0.39	0.33	0.36
	SE	0.43	0.63	0.71	1.20	0.55	0.71	1.04	1.20	1.30	1.58	1.46	1.53
	SEE	7.06	6.95	6.85	6.32	7.0	6.81	6.54	6.31	6.16	5.62	5.86	5.72

In the present study, the soil moisture was considered constant during the entire growth period of the crop in order to investigate basically the effect of crop variables on the bistatic scattering coefficient. The multiple regression equation may be written as

$$\sigma_{pp}^{0}(dB) = a + b \times Age + c \times PH + d \times VWC + e \times LAI \qquad (5.1)$$

The model coefficients a, b, c, d, and e were determined by fitting the observed bistatic scattering coefficients and corresponding kidney bean crop variables of reference field and are presented in the Table 5.3. Equation (5.1) may be used to generate large sets of bistatic scattering coefficient consistent with the age of kidney bean crop by putting kidney crop variables for its various growth stages. Equation (5.1) is a linear equation with three kidney bean crop variables along with its age. Therefore, it may have infinite solutions. To have a proper solution consistent with the real growth of kidney bean crop, at least 4 number of equations along with a common factor are needed.

For this purpose, the age of kidney bean crop may be taken as a common factor between kidney bean crop variables and bistatic scattering coefficient. The relation between the growth stages (age) of kidney bean crop with the crop variables is discussed in Section 5.4.2.

Table 5.3 The values of coefficients of equation (5.1) and result of regression analysis

Frequency	Coefficients					Result of linear least square fitting				Pol.
	a	B	c	d	E	R^2	SE	SEE	RMSE	
X-band	-15.66	0.06	0.03	-1.18	0.12	0.9906	0.4545	0.1256	0.1261	HH
X-band	-14.16	0.04	0.07	-0.72	-0.17	0.9940	0.4527	0.0999	0.1002	VV

5.4.2 FITTING OF CROP VARIABLES WITH DIFFERENT AGE OF KIDNEY BEAN CROP

All the kidney bean crop variables at its various growth stages and their corresponding ages of the crop were fitted to the Gaussian function. It shows very good correlation between kidney bean crop variables and the age of the kidney bean crop. The detailed parameters of Gaussian fitting are presented in Table 5.4. Figure 5.1 shows the basic graphical representation of Gaussian function. Figure 5.2 (a-c) shows the graphical representation of Gaussian fitting for all the crop variables of kidney bean. The Gaussian fitting was used to estimate the crop variables of kidney bean at different growth stages of the crop. The Gaussian fitting and multiple regression Equation (5.1) were used to generate the input data sets for the training of artificial neural network.

Mathematically, the Gaussian function is represented by Equation (5.2),

$$y = y_0 + \frac{A}{W\sqrt{\frac{\pi}{2}}} \exp\left(-2\left(\frac{x - x_c}{W}\right)^2\right) \tag{5.2}$$

Where y_0 = baseline offset, A= total area under the curve from the baseline, x_c =center of the peak and $W = 2\sigma$ = the width at half height of the peak.

This model describes a bell-shaped curve like normal (Gaussian) probability distribution function as shown in Figure 5.1. The centre x_c represents the 'mean', while W/2 is the standard deviation.

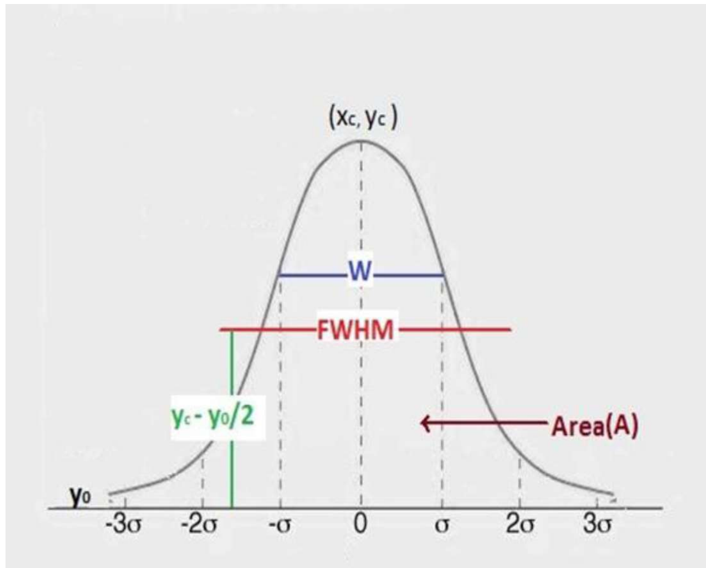


Figure 5.1 Graphical representations of Gaussian function

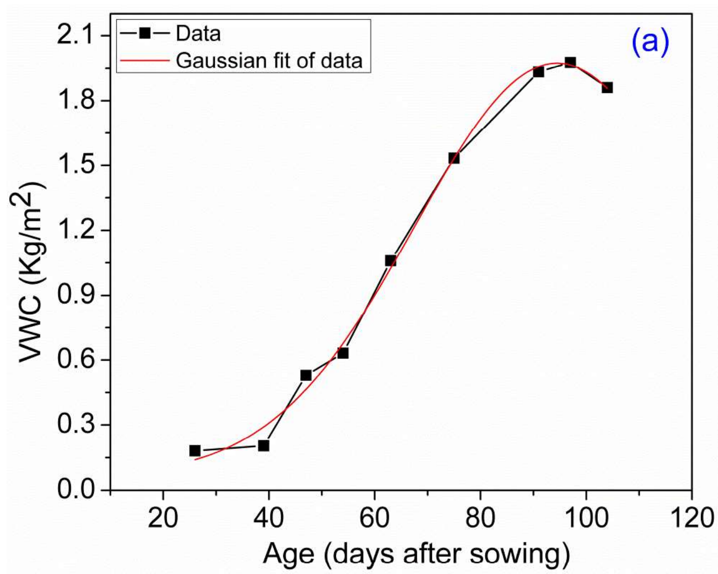
Table 5.4 Values of fitting parameters of Gaussian function for kidney bean crop variables

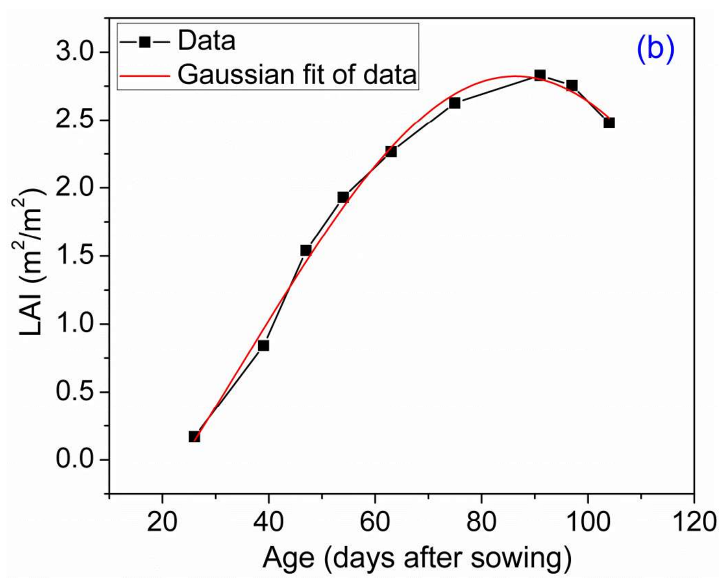
	R^2	y_0	x_c	W	Area (A)	Sigma (σ)	FWHM	Height $(y_c - y_0)$
VWC	0.9937	0.067	94.45	53.58	128.02	26.79	63.08	1.91
LAI	0.9914	-2.64	86.37	103.92	711.83	51.96	122.36	5.47
PH	0.9976	-15.8	92.71	100.53	8091.74	50.27	118.37	64.22

5.5 ARTIFICIAL NEURAL NETWORK

The artificial neural networks (ANN) based on gradient descent algorithm, were used for the estimation of kidney bean crop variables. The ANN model was developed with 1 neuron at input layer, 10 neurons at hidden layer and 4 neurons at the output layer for the estimation of kidney bean crop variables.

The ANN model consists of one hidden layer. The hyperbolic tangent transfer function (*tansig*) was used as an activation function at hidden layer neurons. The linear transfer function (*purelin*) was used as an activation function at the output layer neurons. The learning rate was taken 0.6 for both the ANN models. Figure 5.3 shows the architecture of ANN model used in our investigation.





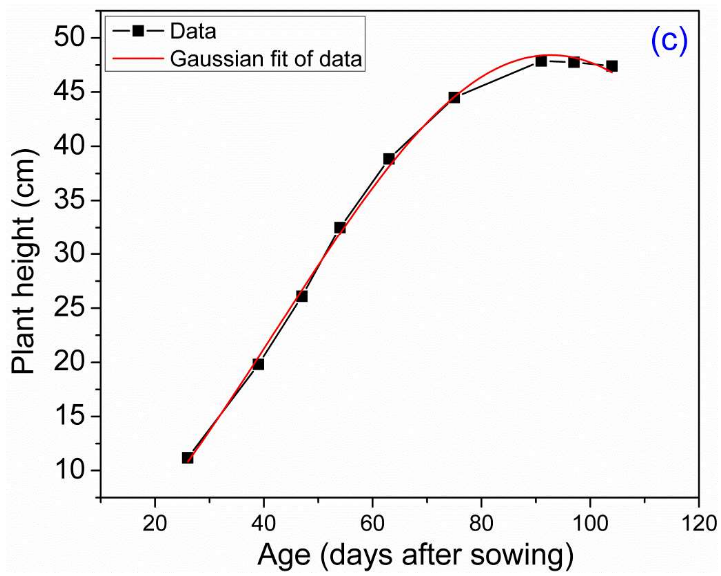


Figure 5.2 (a-c) Temporal variation of VWC, LAI and plant height of kidney bean crop fitted with Gaussian function

The training of the ANN model was done by feeding a pair of vectors namely the input vector containing simulated bistatic scattering coefficient and the output vector containing simulated kidney bean crop variables. The set of training vectors were generated by using the empirical models as described in Sections 5.4. The training with the input data simulated by empirical models allows varying input and output parameters freely within the established bounds ensuring the consistency of the training data (Dawson 1994). The simulated data sets (bistatic scattering coefficients and kidney bean crop variables) were consistent with the age of kidney bean crop. Total 95 data sets were generated for each day between 26 to 120 days after sowing of kidney bean crop. The observed data set of the second crop bed of kidney bean was used for the estimation of kidney bean crop variables and validation of ANN model.

5.6 RESULT AND DISCUSSIONS

5.6.1 ANGURAL VARIATION OF BISTATIC SCATTERING COEFFICIENT

Figure 5.4 (a-d) shows the temporal variation of crop variables (i.e. VWC, LAI, PH & SPAD value) at the various growth stages of kidney bean crop. Figure 5.5 shows the photographs of kidney bean crop for its various growth stages. All the crop variables were found to increase with the age of crop. The VWC was found to increase until 97 days after sowing and then started slight decreasing with the beginning of fruit filling stage. The PH increased sharply till 91 days and then after it was slowed down. The LAI was found to increase sharply after 60 days of sowing and continued till 91 days (fruit filling stage). SPAD value increased monotonically at the initial growth stages and decreased at latter stages of the growth of crop kidney bean. Average crop covered SM in the field was found to be 20.93% gravimetric.

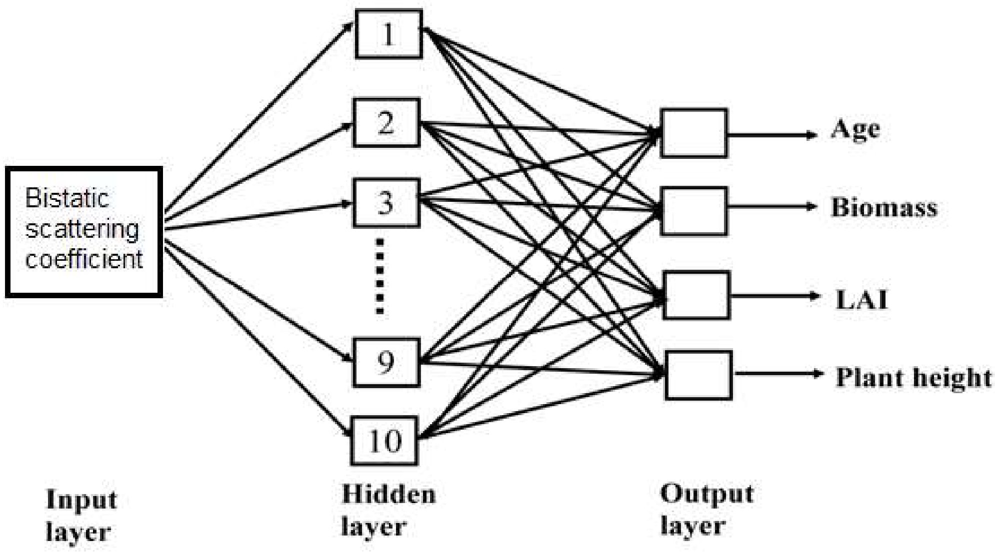


Figure 5.3 Architecture of ANN model used in the present study

The angular variation of bistatic scattering coefficients at various growth stages of the kidney bean crop at like polarizations (HH-& VV-) are shown in Figures 5.6 and 5.7 for X- band respectively. The magnitudes of bistatic scattering coefficients were found to decrease with the incidence angle at each growth stage of the kidney bean crop for both like polarization. The difference in dynamic range of bistatic scattering coefficient at various growth stages of kidney bean crop was found sufficient to discriminate the effect of soil moisture and crop variables of kidney bean.

At X-band, when the crop variable were small (VWC= 0.18 kg/m^2, LAI= 0.17 m^2/m^2, PH = 11.2 cm and SPAD value= 27.8) after 26 days of sowing, the dynamic ranges of bistatic scattering coefficient were found to be 5.59 dB and 7.64 dB at HH- and VV-polarizations, respectively. Whereas, when the crop variables were high

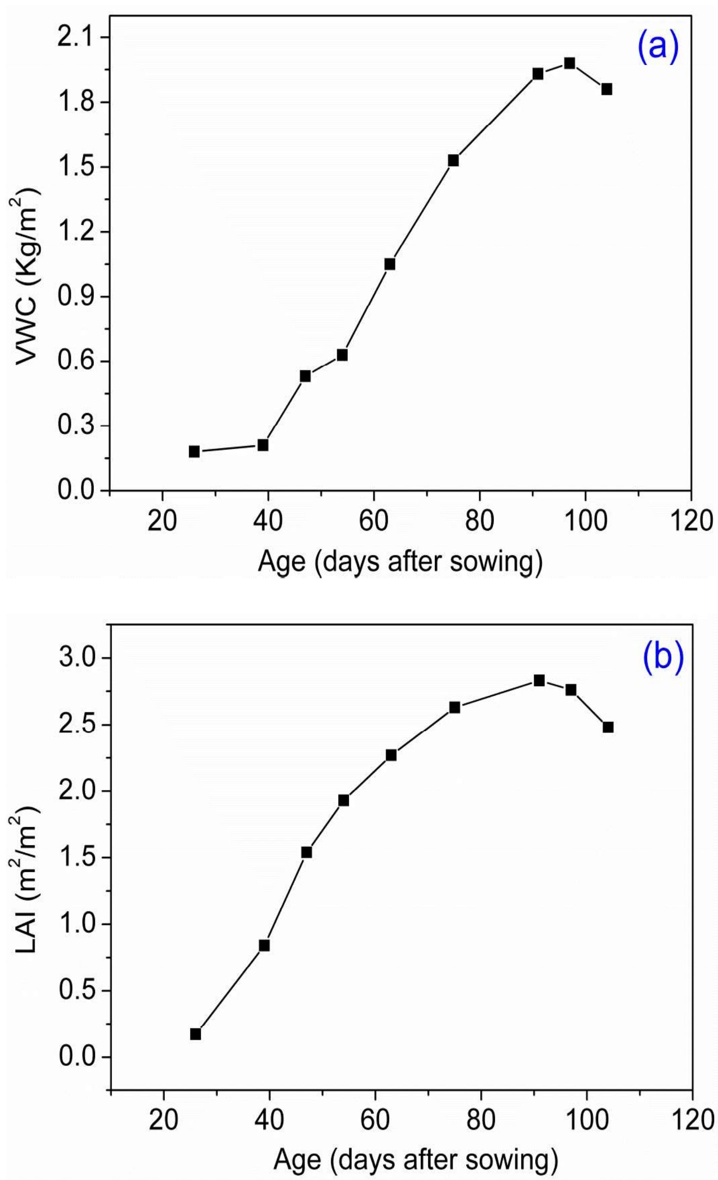
(VWC= 1.98 kg/m^2, LAI= 2.76 m^2/m^2, PH = 49.2 cm and SPAD= 35) after 97 days of sowing, the dynamic ranges of bistatic scattering coefficient were decreased to 2.16 dB and 2.45 dB at HH- and VV-polarizations, respectively.

At the early age of kidney bean crop, when the values of crop variables were small, the dynamic range of bistatic scattering coefficient was found to be greater than that of older age of the crop. Therefore, at the early age of crop, soil moisture effect on bistatic scattering coefficient was found to be more prominent than the crop effect. The decrease in the dynamic range of bistatic scattering coefficient with the age of crop indicates the dominance of the crop effect relative to the soil moisture effect at the latter growth stages of the crop. Thus, angular trends were flatter with the age of crop because the effects of the soil were screened by the developing vegetation parameters. Similar observations have been reported by the earlier researchers (Cramer et al. 2001; Prasad 2009; Wang and Qu 2009) using X-, C- and L-band.

Table 5.2 shows the linear regression results for the angular variation of bistatic scattering coefficient with the crop variables at HH- and VV- polarization for X-band. The value of coefficient of determination (R^2) shows the percentage of dependence of bistatic scattering coefficient on the crop variables. The maximum values of R^2 were found to be 0.91 (50°), 0.86 (60°), 0.95 (50°) and 0.22 (50°) at HH-polarization, whereas, in the case of VV-polarization, the maximum values of R^2 were found to be 0.92 (50°), 0.87 (50°), 0.88 (40°) and 0.39 (50°) for VWC, LAI, PH and SPAD value at X-band, respectively.

The values of R^2 for angular variation of bistatic scattering coefficient with the crop variables of kidney bean showed higher values for VV-polarization in comparison to HH- polarization. The microwave signal at high frequency (e.g. 10 GHz) is mainly sensitive to plant parameters such as plant biomass, leaf area index, plant height and percentage of vegetation cover**.** In general, the total scattering coefficient at the higher frequencies such as Ku- and X- band is dominated by the canopy scattering, while at lower frequencies such as L- band and P- band, it is dominated by the crop- covered soil moisture (Vapnik et al. 1997).

All the crop variables, except LAI showed good correlation at incidence angle 50°.Whereas, LAI showed good correlation at incidence angle 40° for VV- polarization. Therefore, in the present study, the configurations of bistatic scatterometer system were chosen to be 50° incidence angle and VV- polarization for the estimation of kidney bean crop variables.



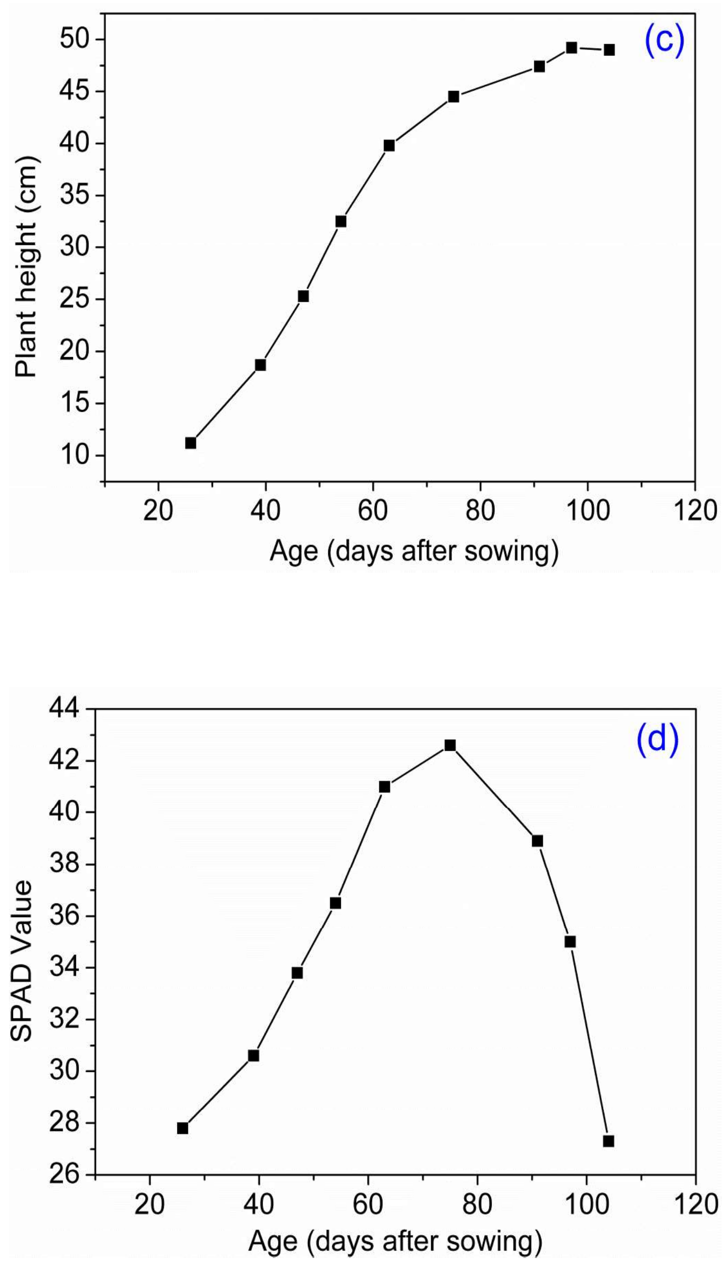


Figure 5.4 Temporal variation of kidney bean crop variables for (a) VWC (b) LAI (c) plant height and (d) SPAD value

Figure 5.5 Photographs of various growth stages of kidney bean crop

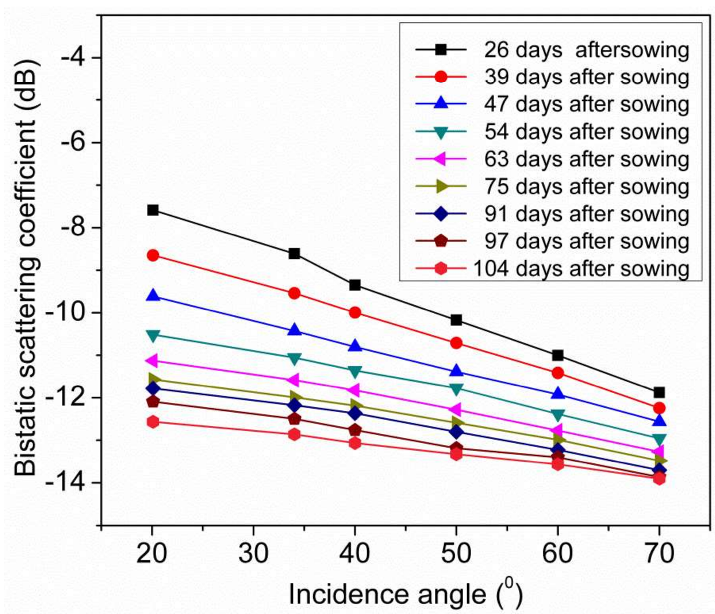


Figure 5.6 Angular variation of bistatic scattering coefficients for kidney bean crop at different growth stages for HH- polarization

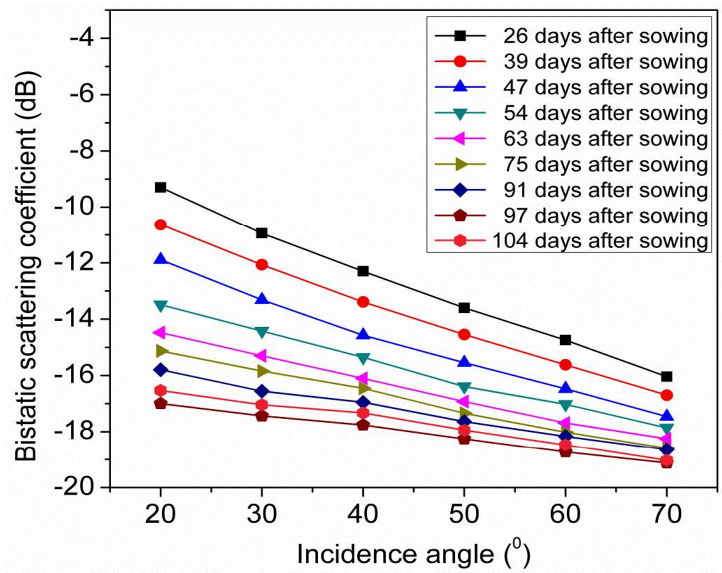


Figure 5.7 Angular variation of bistatic scattering coefficients for kidney bean crop at different growth stages for VV-polarization

5.6.2 RETRIEVAL ALGORITHM FOR THE CROP VARIABLES OF KIDNEY BEAN

The retrieval algorithm for the crop variables of kidney bean is presented in Figure 5.8. The ANN model described in Section 5.5 was used to solve the inversion problem. The following steps were adopted for the estimation of crop variables of kidney bean using scatterometer data.

5.6.2.1 SELECTION OF SUITABLE SCATTEROMETER CONFIGURATION

The linear regression analysis was carried out to determine the suitable incidence angle and polarization of the bistatic scatterometer for the accurate estimation of crop variables of kidney bean.

5.6.2.2 GENERATION OF INPUT DATA SETS FOR THE TRAINING OF ANN BY EMPIRICAL MODELS

The crop variables of kidney bean observed in the reference field at the several growth stages were fitted to the Gaussian function. The estimated values by the developed Gaussian function and observed values of crop variables of kidney bean were found well correlated as reported in the Figure 5.2 (a-c). The 95 data sets of crop variables were generated by the Gaussian functions consistent with the age of the crop for each day between 26 to 120 days after sowing of kidney bean crop. The crop variables estimated by the Gaussian function at various growth stages may be assumed to be the representative of crop variables of entire growth of kidney bean crop. The Equation (5.1) was used to generate the 95 data sets of bistatic scattering coefficient with respect to the age of crop and corresponding values of crop variables. Thus, total 95 multi-temporal data sets (bistatic scattering coefficients and crop variables) were generated at 50° incidence angle, 10 GHz and VV-polarization. These generated multi-temporal data sets by the empirical models (discussed in Section 5.4) were used for the training of ANN model. The bistatic scattering coefficient and crop variables of kidney were used as the input and output data set for the training of ANN model, respectively.

5.6.2.3 TRAINING OF ANN MODEL

A multilayer back propagation artificial neural network algorithm was trained (ANN model) for the estimation of crop variables. The detailed architecture of ANN model is discussed in the Section 5.5. The training of ANN model was done by using the data sets generated through empirical models as discussed in the Section 5.4.

5.6.2.4 ESTIMATION OF CROP VARIABLES (INVERSION PROBLEM)

The observed bistatic scattering coefficient at various growth stages of kidney bean crop sown in the second field were used for the evaluation of the ANN model by estimating the crop variables. Figure 5.9 shows the estimated and observed values of crop variables of the kidney bean sown in the second field. The performance of the developed ANN model was found very good for the estimation of crop variables of the kidney bean.

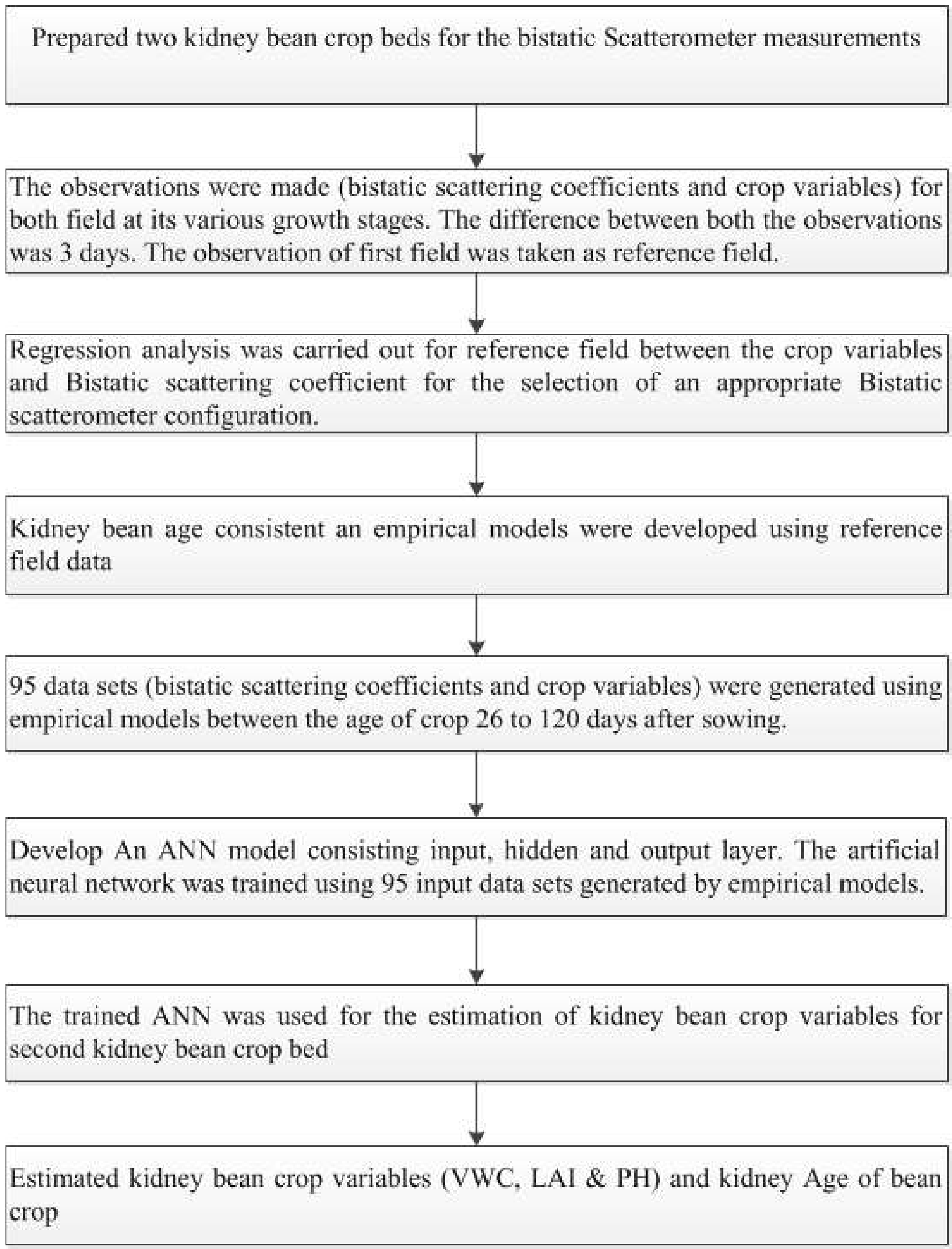
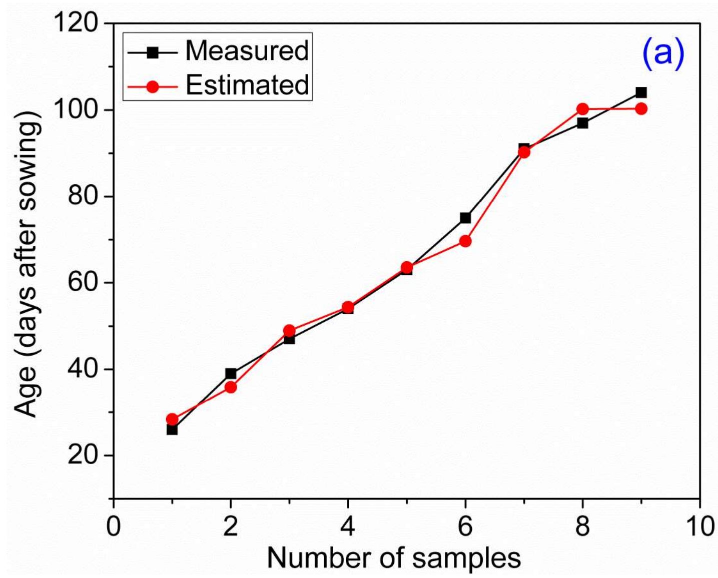
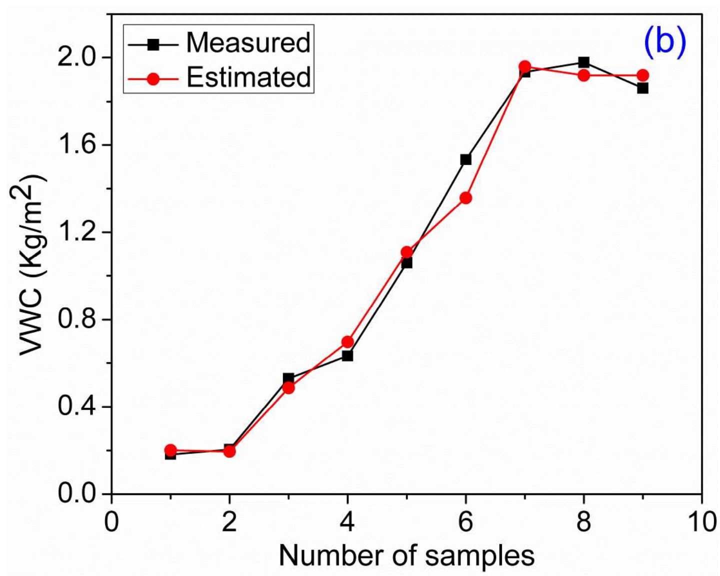
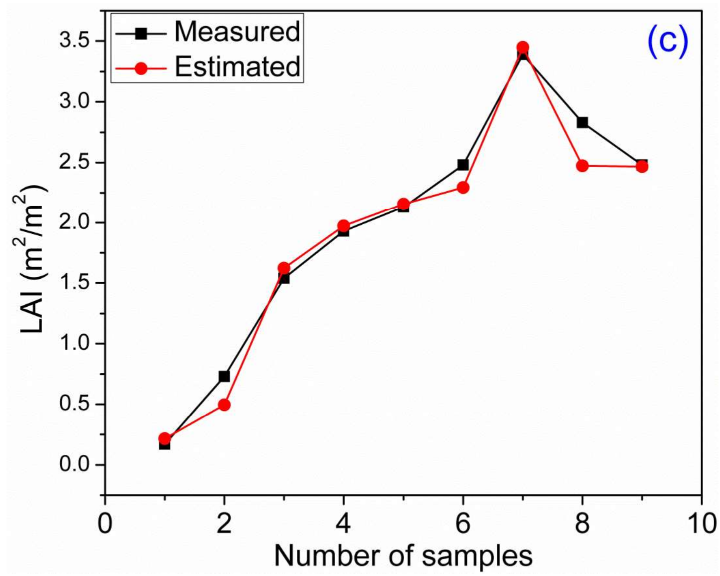


Figure 5.8 Flow chart of algorithm used for the estimation of kidney bean crop variables


Measured
Estimated
(a)
Age (days after sowing)
Number of samples


Measured
Estimated
(b)
VWC (Kg/m2)
Number of samples



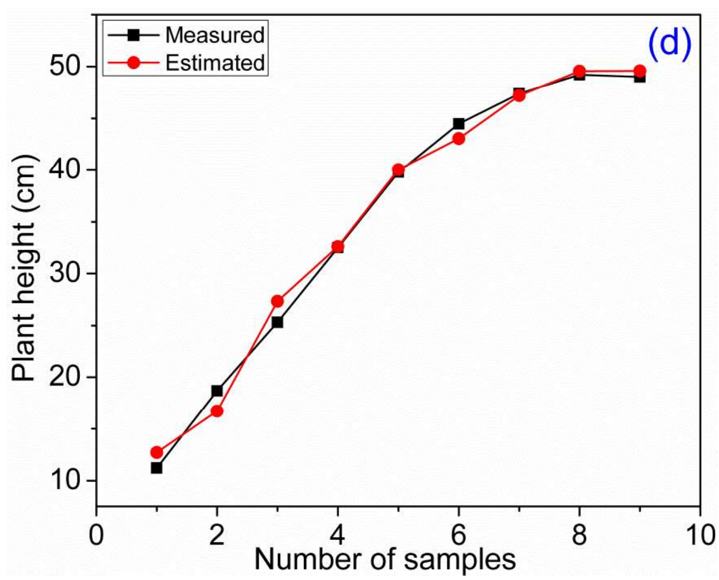


Figure 5.9 (a-d) Estimated crop variables and age of kidney bean by ANN model Vs observed crop variables and age of kidney bean of the second crop bed

5.7 CONCLUSIONS

The suitable configuration of bistatic scatterometer system for the accurate estimation of crop variables was found to be 50° incidence angle, 10 GHz frequency and VV-polarization by the regression analysis. The estimated values by the empirical models were found well correlated with the observed values of bistatic scattering coefficient and crop variables of kidney bean. The developed empirical models can generate the bistatic scattering coefficient and crop variables consistent with the age of kidney bean crop for the training of ANN model. Hence, the prior knowledge about the soil surface properties and vegetation status are not required for the training of artificial neural network used for the estimation of crop variables of kidney bean. The estimated values by the ANN model were found very close to the observed values of crop variables of the kidney bean of the second crop bed used for the testing of developed ANN model. An approach of training of ANN by empirical models consistent with the age of the kidney bean crop proves to be quite effective for the estimation of crop variable.