CHAPTER - 7

ESTIMATION OF CHICKPEA CROP VARIABLES USING BISTATIC SCATTEROMETER DATA AND ARTIFICIAL NEURAL NETWORKS

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7.1 INTRODUCTION

Chickpea legume is a very important cold season diet of billions of peoples living in South Asian countries and especially in India. Chickpea is cultivated on approximate 15% area of the total pulse area in the world of 52 countries (FAO, 2012). Worldwide South and Southeast Asia alone contribute about 88% and 86% production of chickpea respectively. Chickpea is the largest pulse crop grown in India.

As the importance of chickpea crop, it is necessary to gather the information related to the cropping pattern, crop health and change in cultivated area for any country on regular basis. Several researchers have been reported the efficient use of multispectral and multi-temporal data to develop the protocols and methods for monitoring of major crops such as rice, wheat, sugarcane and maize. Limited studies have been carried out to identify the chickpea sown areas and its monitoring. Gupta et al.(2006) reported hyperspectral ratio and normalized difference vegetation indices by computed using ground-based spectral data in 400-950 nm wave length region at various growth stages of wheat and chickpea crop. A regression analysis was carried out for LAI with all possible combinations of hyperspectral ratios and normalized difference indices. The hyperspectral ratios and normalized difference indices showed the strong relationship with LAI. Gumma et al.(2016) have reported the map of temporal changes and spatial distribution of chickpea cropped area over the last decade (2001-2012) in Andhra Pradesh, India using MODIS data. They found significant growth in the chickpea growing areas was observed in the four district of Andhra Pradesh between 2001 and 2012.

The numerous microwave remote sensing studies have been proven for crop type classification and estimation of crop variables (Bouvet et al. 2009; Brown et al. 2003; Le Toan et al. 1997; Li et al. 2011). However, an accurate estimation of crop variables by radar data requires numerous biophysical and soil parameters. These models are very complex to solve or require a large number of input data to retrieve the crop variables. It is needed to find are such type of computational technique for the retrieval of crop growth parameters, which have less time consuming and less complex. The artificial neural network is most effective computational technique used for the retrieval of crop growth parameters (Benediktsson et al. 1997; Civco 1993; Erbek et al. 2004; Foody 1995; Foody et al. 1995; Frizzelle and Moody 2001; Kumar et al. 2015), hydrology (Chang and Islam 2000; Gupta et al. 2014; Hsu et al. 1995; Jiang and Cotton 2004) and agriculture(Chen and McNairn 2006; Del Frate et al. 2003; Jia et al. 2013; Jin and Liu 1997; Pandey et al. 2010; Pandey et al. 2012).

Retrieving crop variables is a fundamental application of radar remote sensing using backscattered signal from the vegetated areas. Several experimental and theoretical studies have demonstrated that the backscattering coefficient is sensitive to crop variables. However, limited studies have been done on bistatic measurement for the monitoring of agricultural crops.

The present study presents bistatic scattering signature from various growth stages of chickpea crop at X-band for HH- and VV-polarization. The artificial neural network was used to estimate the chickpea crop variables. The objectives of the present study were (i) to determine the suitable bistatic scatterometer configuration for the accurate estimation of chickpea crop variables using artificial neural network (ii) to estimate the chickpea crop variables using bistatic scatterometer data and artificial neural network.

7.2 METHODS AND OBSERVATIONS

The detailed procedure and specifications of bistatic scatterometer and chickpea crop variable measurement are discussed in Chapter 2. The chickpea crop attained maximum average height of 34 cm in our crop bed during the entire observations. The maturity age of crop was found to be 104 days after the date of sowing. The measured values of chickpea crop variables and soil moisture at 12 different growth stages are presented in the Table 7.1.

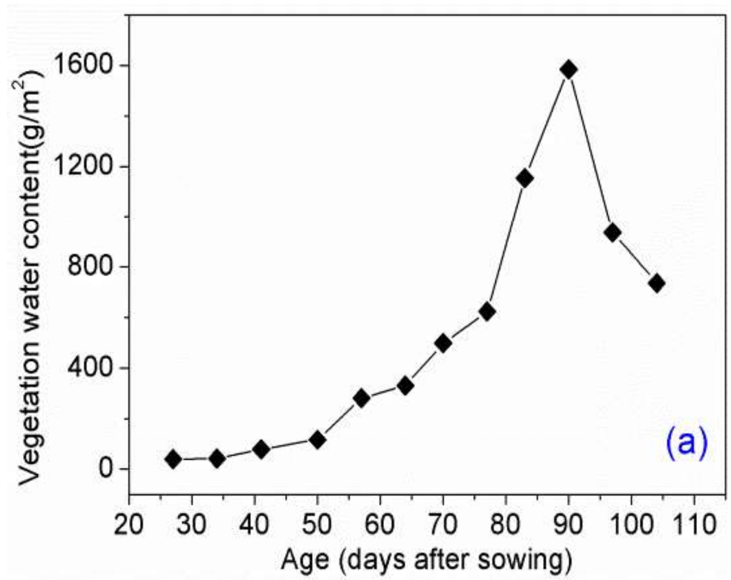
Figure 7.1 (a-c) shows the temporal variation of chickpea crop variables like VWC, LAI, biomass and PH at its different growth stages. Figure 7.2 shows the photographs of chickpea crop at its various growth stages. All the crop variables were found to increase with the age of crop. At the early growth stages of chickpea crop, the VWC was found to increase slowly until 50 days after sowing and then started increasing rapidly up to 90 days after sowing after it started decreasing. The LAI of chickpea crop is found to increase sharply until 57 days and then it increased slowly up to 83 days of sowing and finally found decrease. The plant height increases continuously till 90 days after sowing of chickpea crop and then after it attend approximately constant or small decreasing behavior till the maturity. Average crop covered soil moisture (SM) in the crop bed is found to be 11.43% gravimetric.

Table 7.1 Chickpea crop variables at its various growth stages

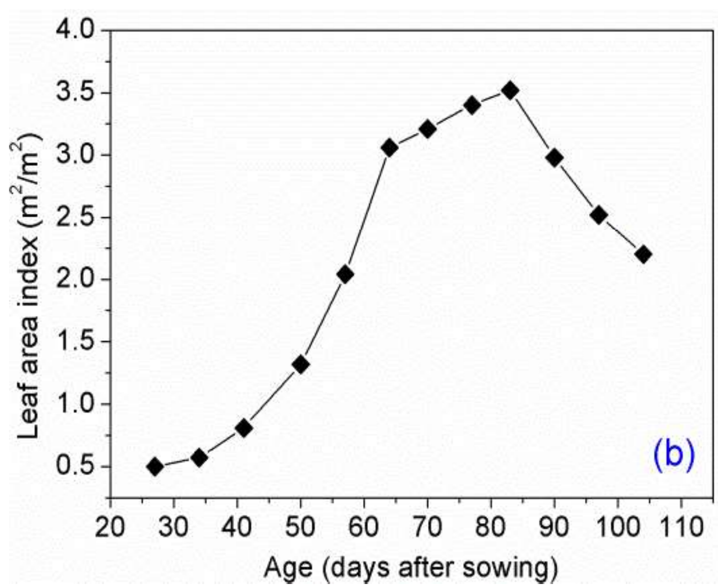
Days after sowing		27	34	41	50	57	64	70	77	83	90	97	104
LAI		0.50	0.57	.81	1.32	2.04	3.06	3.21	3.40	3.52	2.98	2.52	2.20
Biomass (g/m^2)	Wet	161	142.6	192.3	261.3	403.9	606.3	778	908.9	1592	2140	1534	1273.2
	Dry	122	100	115	143.9	121.4	274.2	279	284.3	438	554.8	597.8	535.9
VWC (g/m^2)		39	42	77.3	117.3	282.4	332.1	499	624.7	1154	1585	936.2	737.4
Plant height (cm)		11.9	15	18	20	23	28	29	30	34	33	33	31
SPAD Value		52.6	57.2	55.3	50.6	55.2	59.4	58.2	58.7	56.3	57.1	36.9	36.9
SM (%)		11.3	11.4	11.5	10.3	10.3	11.4	11.9	12.5	12.1	10.1	12.2	12.2

7.3 LINEAR REGRESSION ANALYSIS

The linear regression analysis is done between chickpea crop variables and bistatic scattering coefficient at different incidence angles for HH- and VV-polarizations. It is done to find the suitable incidence angle at HH- and VV-polarization for the estimation of chickpea crop variables. Table 7.2 and 7.3 show the linear regression results between bistatic scattering coefficients and the chickpea crop variables at different configuration of bistatic scatterometer system. The 50° incidence is found suitable for the estimation of chickpea crop variables at HH- and VV-polarization by comparing the values of coefficient of determination (R^2).



Vegetation water content(g/m^2)
1600
1200
800
400
0
(a)
20
30
40
50
60
70
80
90
100
110
Age (days after sowing)



Leaf area index (m^2/m^2)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
(b)
20
30
40
50
60
70
80
90
100
110
Age (days after sowing)

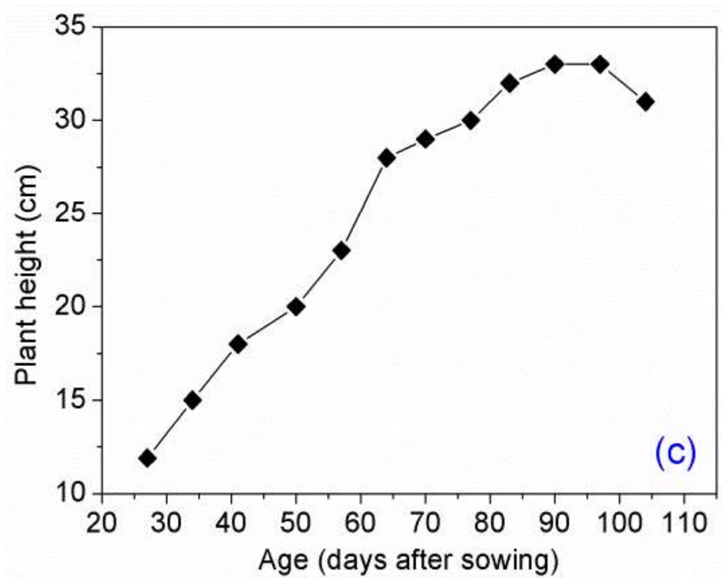


Figure 7.1 Temporal variations of chickpea crop variables for (a) VWC (b) LAI (c) plant height

Figure 7.2 Photographs of wheat crop at various growth stages

7.4 RESULT AND DISCUSSIONS

7.4.1 TEMPORAL VARIATION OF BISTATIC SCATTERING COEFFICIENTS

Figures 7.3 and 7.4 show the angular variation of bistatic scattering coefficients at various growth stages of the chickpea crop for like polarizations (HH- & VV-) at X-band, respectively. The magnitudes of bistatic scattering coefficients were found to decrease with the incidence angle at each growth stage of the chickpea crop for both the polarizations. The soil moisture content in the crop bed was taken constant during each observation to discriminate the vegetation and soil moisture effect in bistatic scatterometer data.

When the values of chickpea crop variable were small (VWC= 39 g/m^2, LAI= 0.5 m^2/m^2, PH = 1.9 cm) after 27 days of sowing, the dynamic ranges of bistatic scattering coefficient were found to be 11 dB and 11.50 dB at HH- and VV-polarizations, respectively. Whereas, when the chickpea crop variables were high (VWC= 1585 g/m^2, LAI= 3.52 m^2/m^2, PH = 34 cm) after 90 days of sowing, the dynamic ranges of bistatic scattering coefficient were decreased to 6.46 dB and 5.12 dB at HH- and VV-polarizations, respectively.

Table 7.2 Results of regression analyses between bistatic scattering coefficients and chickpea crop variables at different incidence angles for X-band at HH- polarization

Incidence angle →		20°	30°	40°	50°	60°
VWC	R^2	0.681	0.701	0.716	0.719	0.681
	Std. Err.	117.511	119.210	120.504	120.764	120.829
	Std. Err. Of Est.	266.480	258.045	251.346	249.970	249.624
LAI	R^2	0.876	0.883	0.888	0.885	0.868
	Std. Err.	0.240	0.241	0.241	0.243	0.237
	Std. Err. Of Est.	0.724	0.722	0.719	0.714	0.733
Plant height	R^2	0.553	0.550	0.548	0.560	0.536
	Std. Err.	2.078	2.072	2.063	2.075	2.054
	Std. Err. Of Est.	2.438	2.495	2.573	2.469	2.653

Table 7.3 Results of regression analyses between bistatic scattering coefficients and chickpea crop variables at different incidence angles for X-band at VV-polarization

Incidence angle →		20°	30°	40°	50°	60°
VWC	R^2	0.694	0.691	0.683	0.699	0.691
	Std. Err.	118.641	118.385	117.670	119.084	118.336
	Std. Err. Of Est.	260.915	262.189	265.706	258.684	262.436
LAI	R^2	0.873	0.878	0.880	0.881	0.867
	Std. Err.	0.237	0.239	0.241	0.240	0.240
	Std. Err. Of Est.	0.735	0.726	0.721	0.724	0.723
Plant height	R^2	0.534	0.545	0.547	0.551	0.549
	Std. Err.	2.061	2.066	2.069	2.069	2.053
	Std. Err. Of Est.	2.598	2.548	2.522	2.524	2.661

At the early age of chickpea crop 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.

Tables 7.2 and 7.3 show the linear regression results for the angular variation of bistatic scattering coefficient with the crop variables for like polarizations at X-band. The value of coefficient of determination (R^2) shows the percentage of dependence of bistatic scattering coefficient on the crop variables. All the crop variables and bistatic scattering coefficients showed good correlation at higher incidence angles. The maximum values of R^2 were found at 50^0 incidence angle for all the crop variables at HH- and VV- polarization. The values of R^2 for angular variation of bistatic scattering coefficient with the crop variables of chickpea showed higher values for HH-polarization in comparison to VV- polarization for all the crop variables.

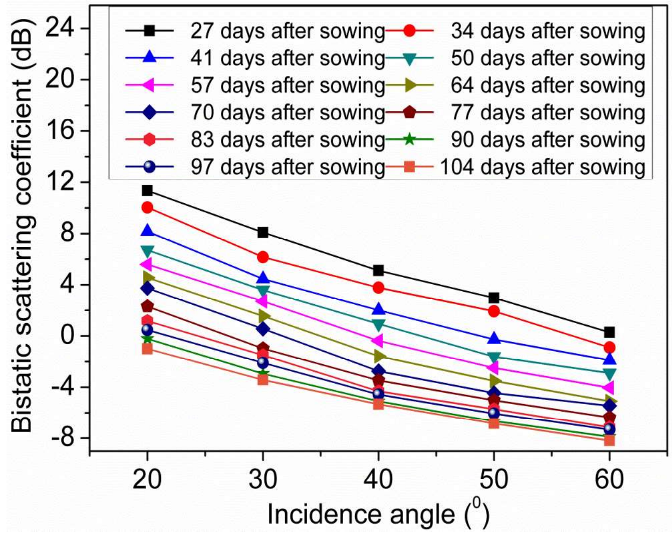


Figure 7.3 Angular variation of bistatic scattering coefficient for chickpea crop at different growth stages for HH- polarization at X-band

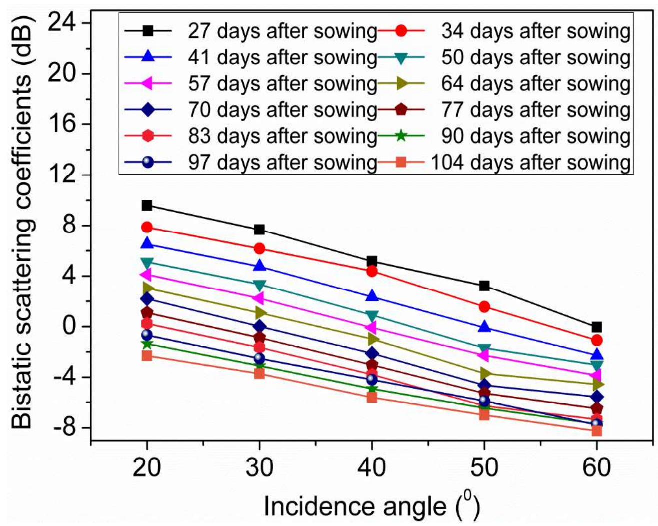


Figure 7.4 Angular variation of bistatic scattering coefficient for chickpea crop at different growth stages for VV- polarization at X-band

7.4.2 ESTIMATION OF CHICKPEA CROP VARIABLES

The retrieval process of the chickpea crop variables is presented in Figure 7.5. The following steps were adopted for the retrieval of chickpea crop variables using bistatic scatterometer data and artificial neural network.

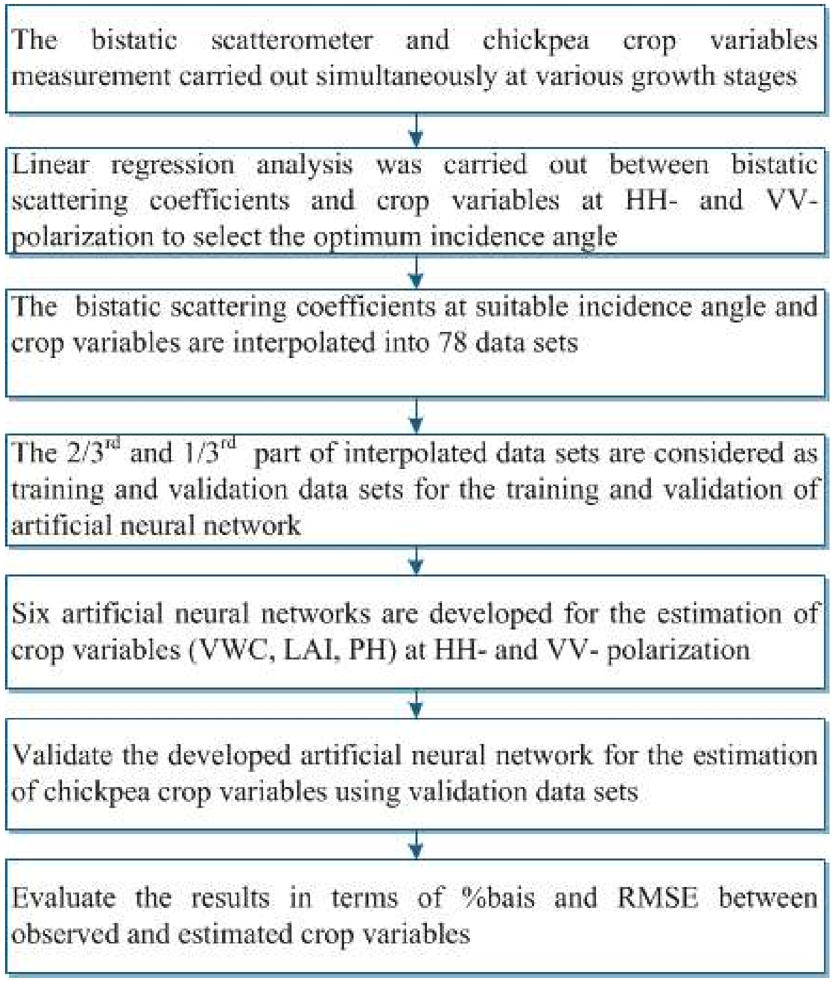


Figure 7.5 Flow chart for the estimation procedure of chickpea crop variables

The linear regression analysis was carried out between bistatic scattering coefficients and chickpea crop variables to determine the suitable incidence angle at HH- and VV-polarizations for the accurate estimation of chickpea crop variables. The values of coefficients of determination (R^2) compare at each incidence angle to select the optimum incidence angle. The higher values of R^2 were found at 50° incidence angle for VWC (0.7165) and PH (0.56012) while the value of R^2 was found maximum at 40° incidence angle for LAI (0.889) at HH- polarization. The higher values of R^2 were found at 50° incidence angle for VWC (0.669), LAI (0.088) and PH (0.551) at VV-polarization.

The bistatic scattering coefficients and chickpea crop variables were interpolated into 91 data sets for each day between 20 to 110 days after sowing of chickpea crop. Thus, the total 91 multi-temporal data sets (bistatic scattering coefficients and chickpea crop variables) were found at 50° incidence angle for HH- and VV-polarization. The 2/3rd part of interpolated data sets were selected for the training and remaining 1/3rd part of interpolated data sets were selected for the validation of developed artificial neural network.

A multilayer back propagation artificial neural network (BPANN) was developed for the estimation of chickpea crop variables. The architecture of developed BPANN model is given in Figure 7.6. The optimum parameters of developed BPANN model for the estimation of chickpea crop variables are presented in Table 6.2. The developed BPANN model contained one input neuron, one hidden layers (10 neurons) and one output neuron. The sigmoid transfer function “tansig” and linear transfer function “purelin” were used for the hidden layer and output layer respectively. The training function Gradient Descent (traingd) and performance function root mean squared error (RMSE) were used for the training and evaluating the performance of BPANN model. Eight multi layers BPANN models were used to estimate VWC, LAI and PH at both HH- and VV- polarization. Figure 7.6 shows the schematic diagram of BPANN model used in the present study.

The validation data sets were used to evaluate the performance of developed BPANN model by estimating the chickpea crop variables at both the polarization. The performance of the ANN models were evaluated in terms of performance indices (coefficient of determination (R^2), RMSE and %bais). The performance indices were computed between estimated values of crop variables by ANN models and crop variables data sets of validation data sets. Figure 7.7 (a-c) show the 1:1 axes plot between estimated values and observed values of each chickpea crop variables at HH-polarization. Figure 7.8 (a-c) show the 1:1 axes plot between estimated values and observed values of each chickpea crop variables at VV-polarization. These figures also show the values of performance indices between estimated and observed values of chickpea crop variables

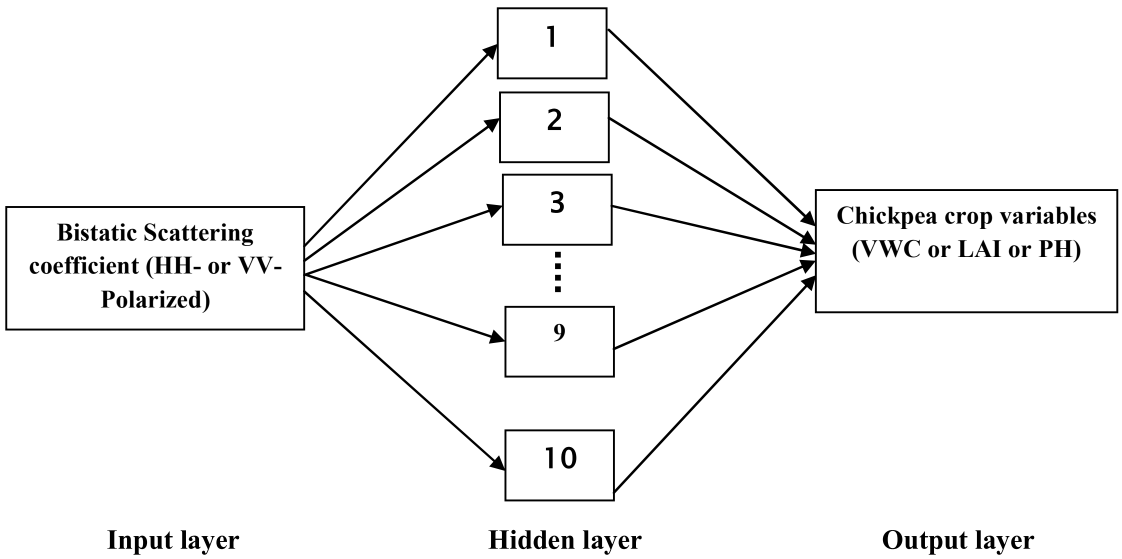
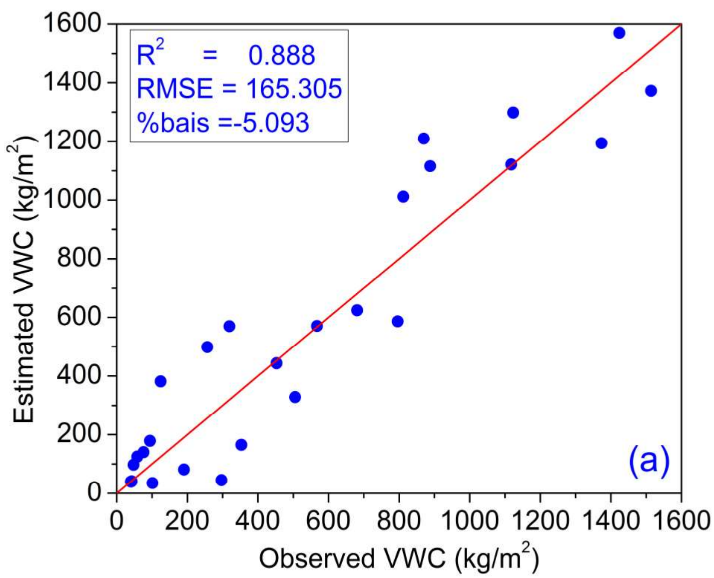


Figure 7.6 Architecture of developed BPANN model

The estimation of LAI was found better than other chickpea crop variables by ANN model at HH- polarization and VV-polarization. The results for the estimation of chickpea crop variables by ANN were found better at VV-polarization than HH-polarization.



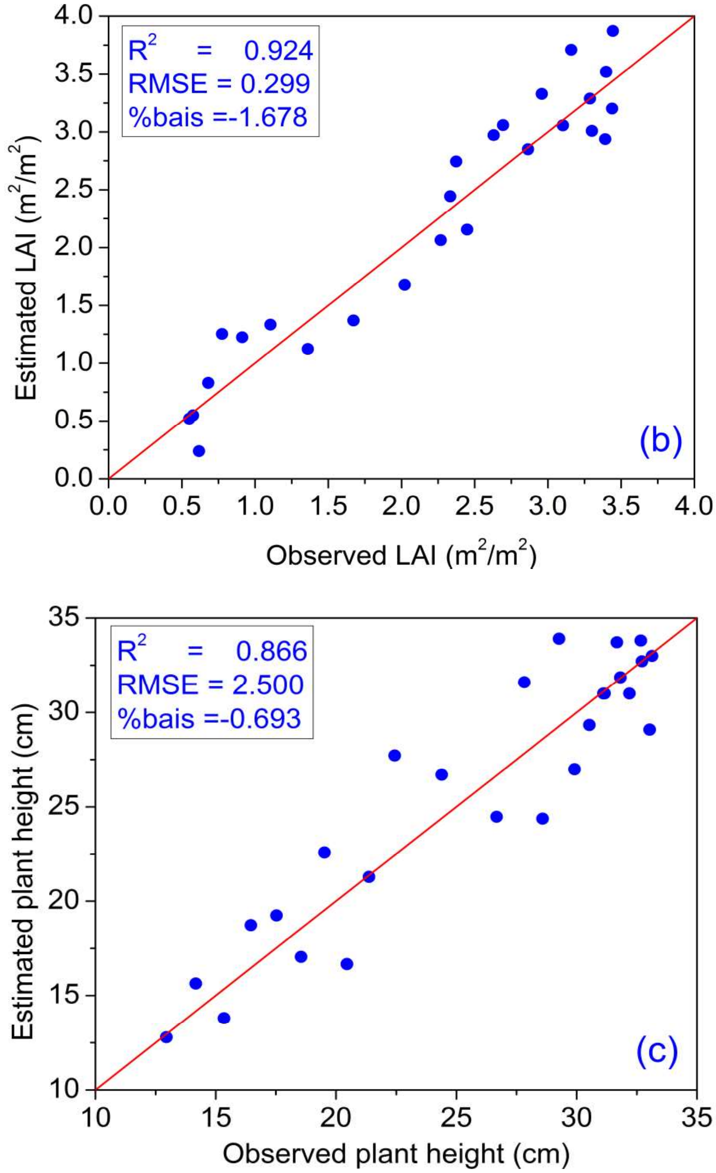
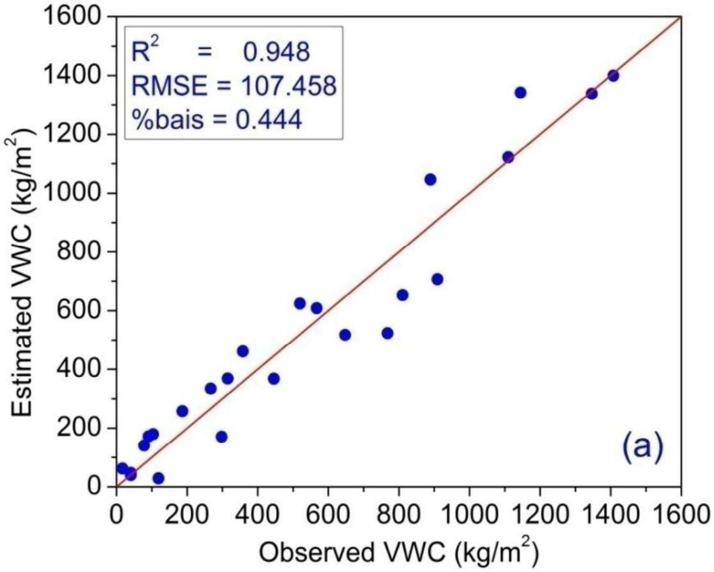
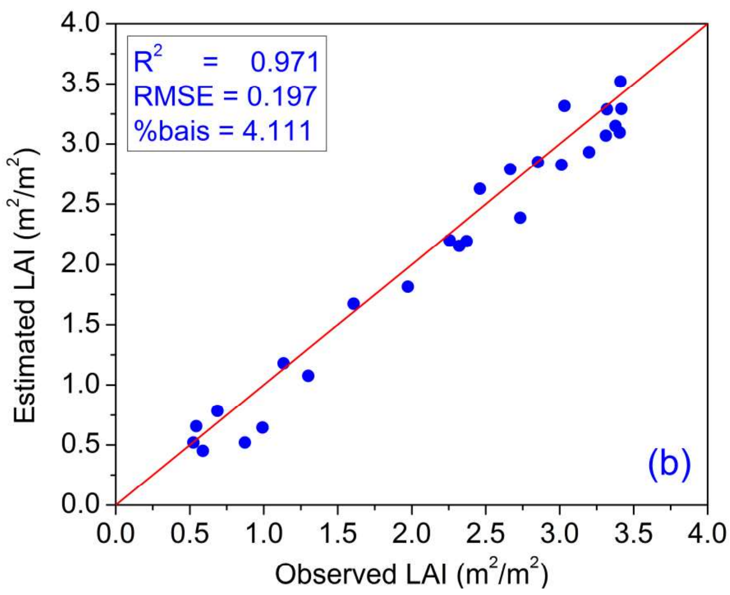


Figure 7.7 (a-c) 1:1 axes plot between estimated crop variables and observed crop variables for (a) VWC (b) LAI (c) PH at HH- polarization



R^2 = 0.948
RMSE = 107.458
%bais = 0.444
(a)
Estimated VWC (kg/m^2)
Observed VWC (kg/m^2)
0
200
400
600
800
1000
1200
1400
1600



R^2 = 0.971
RMSE = 0.197
%bais = 4.111
(b)
Estimated LAI (m^2/m^2)
Observed LAI (m^2/m^2)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

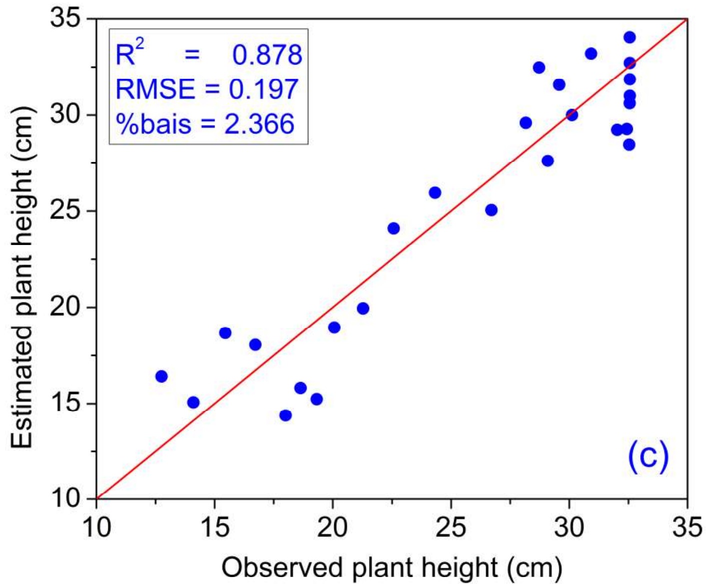


Figure 7.8 (a-d) 1:1 axes plot between estimated crop variables and observed crop variables for (a) VWC (b) LAI (c) PH at VV- polarization

7.5 CONCLUSIONS

The angular variation of bistatic scattering coefficient was found decreasing trend. The suitable incidence angle was found 50° for the accurate estimation of chickpea crop variables at HH- and VV-polarization. The estimated values by the ANN model were found very close to the observed values of crop variables of the chickpea crop at HH- and VV-polarization. The performance of ANN for the estimation of LAI was found better in comparison of other crop variables at both polarizations. However, the performance of ANN model for the estimation of chickpea crop variables at VV- polarization was found better than HH- polarization.