CHAPTER - 4

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

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4.1 INTRODUCTION

Rice is a worldwide important food crop. The economy of many countries depends on the rice production (Wang et al. 2005). Due to its importance as a great food source, it is necessary to monitor continuously over the full growth period of rice crop by acquiring the accurate and timely information about the crop condition.

The tropical monsoon climate is the main period of rice transplanting and growing for the Asian continent (Chakraborty et al. 2005). The microwave remote sensing is more effective tool for monitoring of rice growth than the optical sensing, because, it works any time and in any weather condition with great potential. The primary advantage of microwave remote sensing is its penetration capability through clouds and to some extent rain(Oh et al. 2009).

Synthetic aperture radar is useful to monitor the growth of rice crop by analyzing ERS-1 data at 5.3 GHz, VV- polarization and at incidence angle 23° (Le Toan et al., 1997). The ERS-1 SAR data of two rice fields has been studied to analyze the temporal variation of radar response. The model has been developed to estimate plant height (PH) and plant biomass (BM) of rice crop variables based on temporal variation of the radar response. Kim et al.(2000) studied the temporal and angular responses of the radar backscattering from rice crop at 9 GHz using ground based scatterometer with three polarizations (HH-, VV-, and HV-) at incidence angles 0-70° and reported the maximum backscattering coefficient of the rice field at an early growth stage of about 43-60 days after the transplanting. Lim et al.(2008) also reported the temporal and multi- angular responses of the radar backscattering from rice crop using ground based C- band (6 GHz) scatterometer with full polarization (HH-, VV-, HV- and VH-) in the angular range of incidence angle 10° - 60°. Kim et al.(2008) studied multi frequency backscattering response from rice crop and found high correlation between backscattering coefficients and rice crop variables at full polarizations (HH-, VV-, VH-, HV-) in the angular range of 20° - 60°. Oh et al.(2009) measured the polarimetric (VV-, HH-, HV-, and VH-) backscattering coefficients of flooded rice field using L- and C- bands at incidence angles 30°, 40°, 50° and 60°.

In agriculture, the estimation of crop variables can be used for monitoring the crop growth and prediction of crop yields. An artificial neural network (ANN) is the best optimization technique over a conventional technique for the estimation of crop variables using remote sensing. Several studies showed the applications of artificial neural network in the field of remote sensing applications on agriculture (Chen and McNairn 2006; Del Frate et al. 2004; Del Frate et al. 2003; Jin and Liu 1997; Karkee et al. 2009; Prasad et al. 2009; Singh et al. 2009; Walthall et al. 2004; Xiao-Hua et al. 2009).

The objective of present investigation is to study the bistatic scattering behavior of rice crop at various growth stages using X- band. Polynomial regression analysis is done to find the suitable incidence angle and polarization for the operation of bistatic scatterometer at both like polarizations. Two types of feed forward back propagation artificial neural networks (FFBPANN) are developed for the estimation of rice crop variables.

4.2 DIFFERENT GROWTH STAGES OF RICE CROP

The life cycle of a rice crop in India depends on the variety of rice crop and the environment conditions. It ranges from 105 to 125 days from transplanting to maturity stage. The temporal knowledge about the rice crop development at various growing stages is important for understanding the radar response (Shao et al. 2001). The whole life of rice crop can be distinguished by the four main growth stages, i.e., 1) sowing-transplanting period; 2) vegetative stage; 3) reproductive stage; and 4) ripening stage(Le Toan et al. 1997). The picture of various growth stages of rice crop is shown in Figure 4.1.

4.3 METHODS AND OBSERVATIONS

4.3.1 BISTATIC SCATTEROMETER MEASUREMENT

The specifications of bistatic scatterometer set-up employed for the outdoor bistatic measurements at various growth stages of rice crop are shown in Table 2.1 and the detailed procedure for the bistatic measurement is discussed in the Chapter 2.

(a)

(b)

(c)

Figure 4.1 Growth stages of rice crop (a) vegetative stage, (b) reproductive stage and (c) repining and maturing stage

4.3.2 RICE CROP VARIABLES MEASUREMENT

Rice crop variables namely vegetation water content (VWC), leaf area index (LAI), plant height (PH), SPAD value , plant density, number of stems per bunch, leaf length, leaf width etc. were measured at 8 different growth stages of rice crop and are summarized in the Table 4.1. The bistatic scatterometer measurements were carried out on the same day of taking observations for rice crop variables at the interval of 10 to 15 days.

The detailed procedure for the measurement of biophysical parameters (biomass, LAI, Plant height, chlorophyll content etc.) of the rice crop at its various growth stages are presented in the Chapter 2.

4.4 PROCEDURE FOR THE ESTIMATION OF RICE CROP VARIABLES

The flow chart of algorithm used for the estimation of rice crop variables is shown in Figure 4.2. The following points are adopted to develop the proposed algorithm.

Table 4.1 Summary of the ground truth data with measurement dates

Date /days after transplanting	Aug.13 /5	Aug.26 /18	Sep. 7 /30	Sep.22 / 45	Oct.7 / 60	Oct.22 / 75	Nov.01 / 85	Nov.21 / 105
VWC (kg/m^2)	0.09	0.45	0.80	1.24	1.69	2.40	2.57	2.42
LAI (m^2/ m^2)	0.32	1.25	1.27	1.39	1.87	1.92	2.12	1.98
SPAD value	43.7	42.2	40.9	36.3	30.8	25.5	16.6	15.5
Plant height (cm)	10.8	24.8	65.6	79	90	101	105	102
Stems per bunch	6	9	11	12	15	17	18	18
No. of leaves per stem	2	2	3	3	3	4	4	4
Bunches per m^2	42	42	42	42	42	42	42	42
Leaf length (cm)	7.45	14.82	18.66	26.42	31.92	34.74	35.47	36.21
Leaf width (cm)	0.163	0.45	0.58	0.80	0.99	1.1	1.2	1.34
Leaf thickness (cm)	0.019	0.019	0.019	0.0193	0.02	0.021	0.024	0.03

4.4.1 POLYNOMIAL REGRESSION ANALYSIS

Polynomial regression (least square method) analysis was done to determine the suitable incidence angle and polarization of the bistatic scatterometer system for the estimation of rice crop variables.

The fourth degree polynomial equation used in the present investigation is

$$y_{fited} = aCP^4 + bCP^3 + cCP^2 + dCP + e \tag{4.1}$$

where CP are the crop variables (VWC, LAI, PH and SPAD value). The coefficients (*a, b, c, d* and *e*) were obtained by using least square method. The values of coefficients of determination (R^2), standard error (SE) and standard error of estimation between bistatic scattering coefficients and rice crop variables are presented in the Table 4.2 and 4.3 at HH- and VV- polarization, respectively.

4.4.2 FEED FORWARD BACK PROPAGATION ARTIFICIAL NEURAL NETWORK (FFBPANN)

In the present study, the feed forward back propagation method is used to train the multilayer perceptron. The simple processing units (neuron) are arranged in different layers as input, hidden and output layers in the FFBPANN models. The input layer propagates information in the forward direction to each node of hidden layer with their synaptic weights. These weighted inputs are added at each node. Each hidden layer computes output corresponding to these weighted sums through linear/non-linear sigmoidal transfer functions (Erbek et al. 2004; Haykin 1994, 1999b).

The back propagation training is a supervised training procedure. In the supervised training procedure, both target inputs and target outputs are provided to the network. The output values computed from each hidden layer nodes become the input values for nodes of the output layer. The weighted sum that are processed through the transfer function become the inputs for the output layer nodes. Such nodes of output layer compute the final output of FFBPANN model corresponding to their inputs. These computed output values are compared with the target output values. Therefore, corresponding error is estimated at the output layer between the computed output values and target output values. The estimated errors are minimized by back propagating the error through the network and adjusting the weights and biases in the hidden and output layers until desired results are achieved. This process is repeated iteratively and connection weights and biases are modified until the convergence reached to an acceptable error. Therefore, back propagation neural network reached very close to the desired result or target value. When the feed forward and back propagation algorithms are used together then they are called as feed forward back propagation artificial neural network (FFBPANN).

4.4.3 DATA PREPARATION

The observed data sets (bistatic scattering coefficient and crop growth variables) were interpolated into 101 data sets at the interval of one day from 5 to 105 days after transplanting of rice crop at 30° incidence angle for HH- and VV-polarization. The interpolated data sets for the various growth stages of rice crop were used for training and testing of FFBPANN models. The 81 data sets (at 6-9, 11-14, 16-19, 21-24, 26-29, 31-34, 36-39, 41-44, 46-49, 51-54, 56-59, 61-64, 66-69, 71-74, 76-79, 81-84, 86-89, 91-94, 96-99, 105 days after transplanting) out of 101 data sets were selected for the training of FFBPANN models and remaining 20 data sets (at 5,10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100 days after transplanting) were used for the testing of the developed FFBPANN models.

The interpolated values of bistatic scattering coefficients for HH- and VV-polarizations at incidence angle 30° were used as input data set and values of crop variables such as VWC, LAI, PH and SPAD value were used as output data set for the training of FFBPANN models.

4.4.4 CREATION OF FFBPANN MODELS

An ANN tool box in MATLAB software was used to create and simulate the FFBPANN models. Two FFBPANN models with slightly different architectures were developed for the estimation of rice crop variables namely FFBPANN-I model and FFBPANN-II model. The FFBPANN-I model contained one input neuron (HH- or VV- polarized scattering coefficient), one hidden layers (10 neurons) and one output neuron (VWC or LAI or PH or SPAD value). The FFBPANN-II model contained two input neurons (HH- and VV- polarized scattering coefficient), one hidden layer (10 neurons) and 4 output neurons (VWC, LAI, PH and SPAD value). The sigmoid transfer function "tansig" and linear transfer function "purelin" were used for the hidden layer and output layer neurons respectively. The training function Levenberg-Marquardt (trainlm) and performance function root mean squared error (RMSE) were used for training and evaluating the performance of both the FFBPANN models. Eight multi layers FFBPANN-I models were used to estimate BM, LAI, PH and CC at both HH- and VV- polarization. The FFBPANN-II model was used to judge the combined effect of both polarizations (HH- and VV-) for the estimation of rice crop variables. The architectures of these developed FFBPANN models may also be defined as (1×10×1) and (2×10×4) FFBPANN models. Figure 4.3 (a-b) showed the schematic diagram of FFBPANN-I model and FFBPANN-II model respectively. The statistical difference between FFBPANN-I model and FFBPANN-II model is presented in the Table 4.4.

Table 4.2 Angular variation of polynomial regression results for HH-polarization

Angle (°)	Vegetation Water Content (VWC)			Leaf Area Index (LAI)			Plant height (PH)			SPAD Value		
	R^2	SE	SEE	R^2	SE	SEE	R^2	SE	SEE	R^2	SE	SEE
20	0.81	0.30	0.38	0.92	0.20	0.15	0.78	11.36	15.75	0.77	3.51	4.9
25	0.86	0.31	0.32	0.95	0.20	0.11	0.85	11.83	13.12	0.87	3.71	3.7
30	0.97	0.33	0.13	0.98	0.20	0.07	0.97	12.64	5.67	0.98	3.94	1.48
35	0.82	0.30	0.37	0.92	0.20	0.14	0.79	11.44	15.32	0.75	3.46	5.21
40	0.60	0.26	0.56	0.78	0.18	0.25	0.61	10.02	21.17	0.53	2.91	7.17
45	0.88	0.31	0.30	0.96	0.20	0.10	0.86	11.90	12.65	0.84	3.67	4.10
50	0.91	0.32	0.25	0.97	0.20	0.08	0.90	12.23	10.24	0.93	3.85	2.64
55	0.89	0.32	0.29	0.95	0.20	0.11	0.87	11.97	12.20	0.89	3.76	3.43
60	0.74	0.29	0.45	0.90	0.19	0.17	0.69	10.66	18.87	0.71	3.37	5.60
65	0.57	0.25	0.58	0.81	0.18	0.23	0.55	9.57	22.58	0.48	2.77	7.55
70	0.70	0.28	0.49	0.87	0.19	0.19	0.66	10.48	19.55	0.62	3.14	6.48

Table 4.3 Angular variation of polynomial regression results for VV- polarization

Angle (°)	Vegetation Water Content (VWC)			Leaf Area Index (LAI)			Plant height (PH)			SPAD Value		
	R^2	SE	SEE	R^2	SE	SEE	R^2	SE	SEE	R^2	SE	SEE
20	0.63	0.26	0.53	0.82	0.18	0.23	0.59	9.87	21.66	0.55	2.97	7.01
25	0.79	0.30	0.40	0.90	0.19	0.17	0.82	11.63	14.29	0.73	3.42	5.41
30	0.90	0.32	0.27	0.95	0.20	0.12	0.90	12.21	10.33	0.91	3.80	3.11
35	0.73	0.29	0.46	0.87	0.19	0.19	0.77	11.32	15.94	0.67	3.27	5.99
40	0.74	0.29	0.45	0.88	0.19	0.18	0.79	11.42	15.41	0.69	3.32	5.82
45	0.77	0.29	0.42	0.83	0.19	0.22	0.88	12.06	11.55	0.82	3.62	4.38
50	0.79	0.30	0.40	0.94	0.20	0.13	0.77	11.30	16.03	0.73	3.41	5.44
55	0.86	0.31	0.33	0.86	0.19	0.20	0.88	12.09	11.34	0.84	3.65	4.18
60	0.78	0.30	0.41	0.83	0.19	0.22	0.82	11.61	14.39	0.76	3.47	5.15
65	0.77	0.29	0.42	0.82	0.19	0.22	0.81	11.60	14.48	0.74	3.43	5.33
70	0.72	0.28	0.47	0.80	0.18	0.24	0.77	11.29	16.09	0.68	3.29	5.92

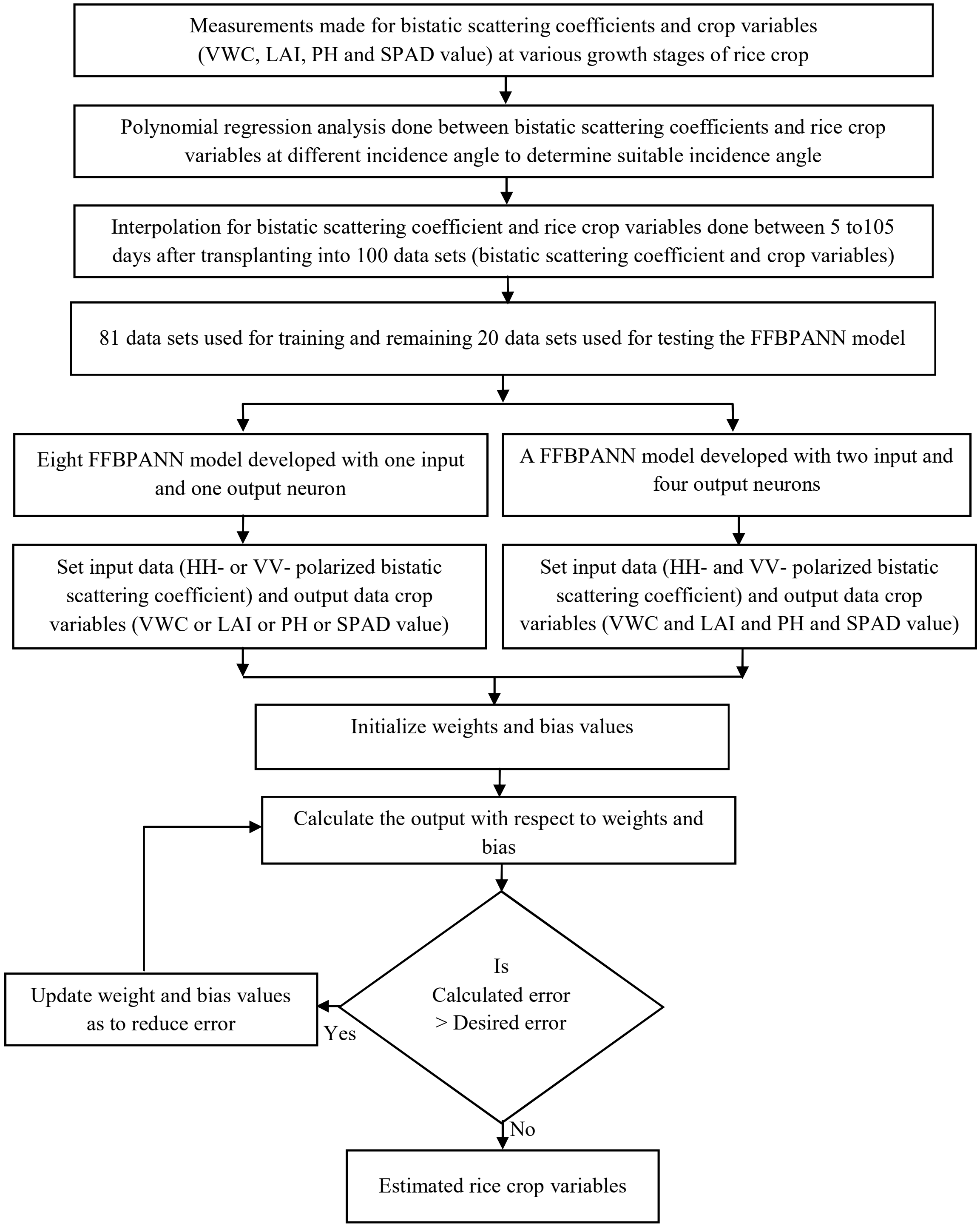
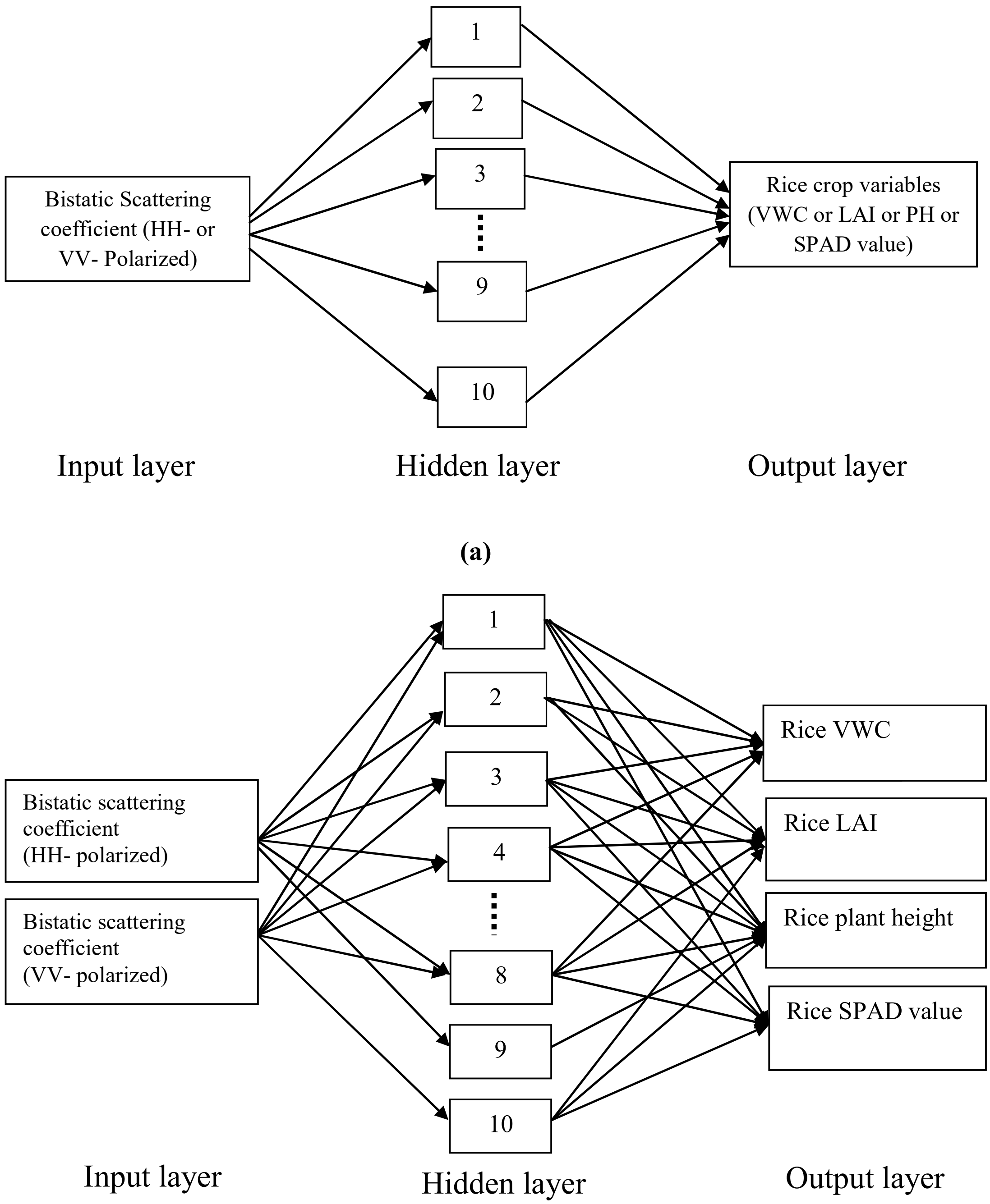


Figure 4.2 Flow chart for the retrieval algorithm of rice crop variables



(b)

Figure 4.3 Architecture of (a) FFBPANN-I model and (b) FFBPANN-II model for the estimation of rice crop variables

Table 4.4 The statistical difference between FFBPANN-I and FFBPANN-II model

FFBPANN parameters	FFBPANN-I	FFBPANN-II
No. of layers	3	3
No. of input layer neurons	1	2
No. of hidden layer neurons	10	10
No. of output layer neurons	1	4
Activation function (hidden layer neurons)	Hyperbolic tangent sigmoid (*tansig*)	Hyperbolic tangent sigmoid (*tansig*)
Activation function (output layer neurons)	Linear *(purelin)*	Linear *(purelin)*
Training rule	Levenberg-Marquardt (*trainlm*)	Levenberg-Marquardt (*trainlm*)
Training data set	81	81
Testing data set	20	20
Learning rate	0.6	0.6
No. of weight connections	20	60

4.5 RESULT AND DISCUSSIONS

The rice crop variables (except SPAD value) were found to increase more rapidly at early stages (60 days after transplanting) of the growth in comparison to the later growth stages. The SPAD value was found higher at early days of the growth and then after started decreasing (Chen et al. 1991a).

Figure 4.4 and 4.5 showed angular variations of bistatic scattering coefficient (σ°) of rice crop at HH- and VV- polarization respectively. Angular variations of bistatic scattering coefficient were computed for eight growth stages from transplanting to maturity stage at the interval of 10 to 15 days after transplanting of rice crop. The bistatic scattering coefficients showed decreasing behavior at vegetative and reproductive stage and then after found increasing behavior at ripening stage (maturity) in the entire angular range of incidence angles at both the like polarizations.

At the vegetative stage, the bistatic scattering coefficient was found dominant due to major contribution of stems and the interaction between the stems and water underneath the rice crop. During vegetative to reproductive stage, the bistatic scattering coefficients were found to decrease until the leaves became large and dense. However, the bistatic scattering coefficient was found to decrease slowly due to random scattering by vertical leaves during reproductive stage. The increase in the size of leaves causes to cover most of the spaces between plants resulted to quench the contributions from the stems and the water underneath. At the ripening stage, the color of leave was found changed from green to yellow and density of leaves was increased. As the crop grew, the angular dependency of bistatic scattering coefficient was found to decrease and it became almost independent near the ripening stage of rice crop.

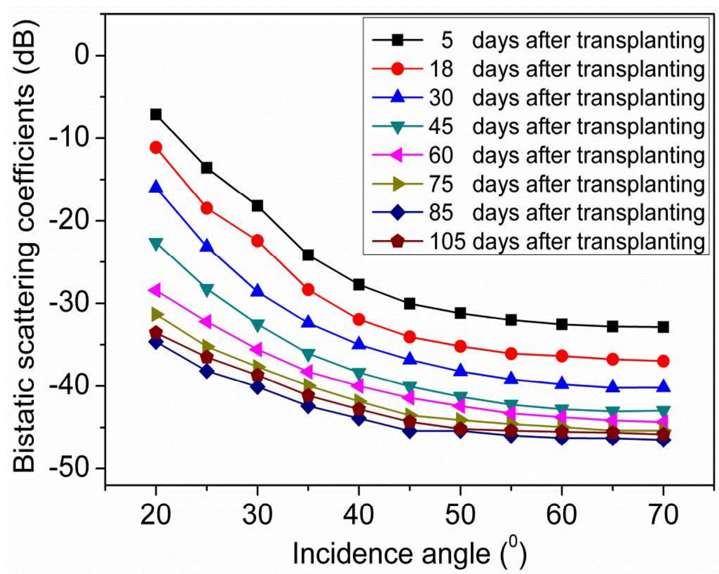


Figure 4.4 Angular variation of bistatic scattering coefficient at different growth stages for HH-polarization

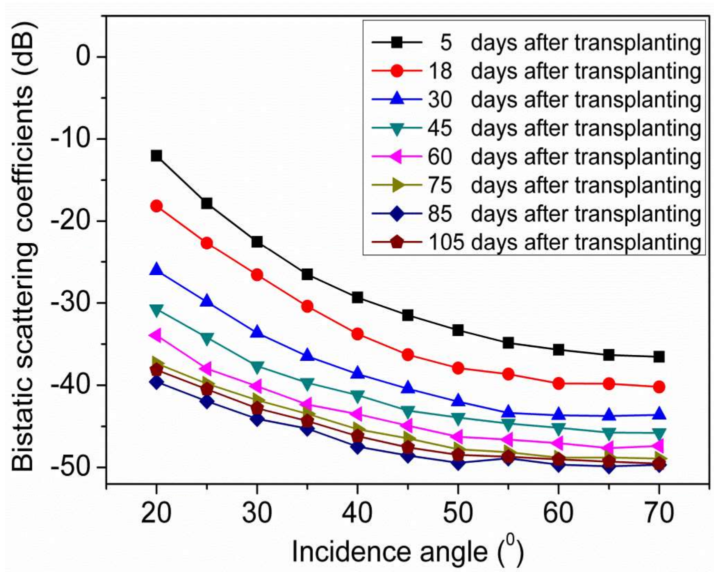


Figure 4.5 Angular variation of bistatic scattering coefficient at different growth stages for VV-polarization

Polarization of a microwave is sensitive to the shape, size and orientation of the targets elements. The horizontal polarization gives the measure of the horizontal dimension, while the vertical polarization gives the measure of the vertical dimension of the scattering elements (Prasad et al. 2009). Thus, the microwave response of different incidence angles due to the change in leave size, its orientation with respect to incidence angle can be used for the effective monitoring of the growth stages of a crop (Chakraborty et al. 2005). For the incidence angles above 30^0, the bistatic scattering coefficient showed a faster decay at VV-polarization than HH-polarization. The attenuation due to vertical cylinders (vertical leaves) at vertical polarization (VV-) was higher than the horizontal polarization (HH-) (de Matthaeis and Lang 2005; De Matthaeis et al. 1994; Lin et al. 2009; Liu et al. 2008).

4.5.1 POLYNOMIAL REGRESSION ANALYSIS FOR SELECTING THE SUITABLE SCATTEROMETER SYSTEM CONFIGURATION

The rice crop variables were fitted with fourth order polynomial to determine the suitable incidence angle and polarization for the estimation of rice crop variables using bistatic scatterometer measurements. Tables 4.2 and 4.3 depict the polynomial regression results for rice crop variables in the angular range of 20° to 70° incidence angles at HH- and VV- polarization respectively. The coefficients of determination

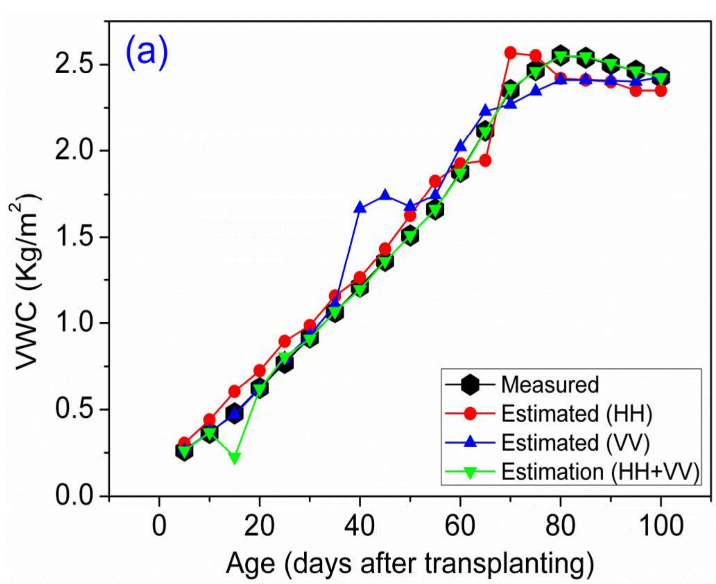
(R^2) were found maximum at 30° incidence angle for all the rice crop variables at HH-polarization and VV-polarization. However, the highest value of coefficients of determination (R^2) was found at 30° incidence angle for all the rice crop variables at HH-polarization. The VV- polarized wave is more attenuated in comparison to HH-polarized wave due to the vertical interaction with the vertical structure of leaves and stems of the rice crop. The wave traveled longer path at higher incidence angle in comparison to lower incidence angle in the crop canopy. Due to this reason, the incident wave was found more attenuated at higher incidence angle in comparison to lower incidence angle. Therefore, the HH- polarization and lower incidence angle were found to be more suitable for accurate estimation of rice crop variables (Bouvet et al. 2009; Inoue et al. 2002; Li et al. 2011)

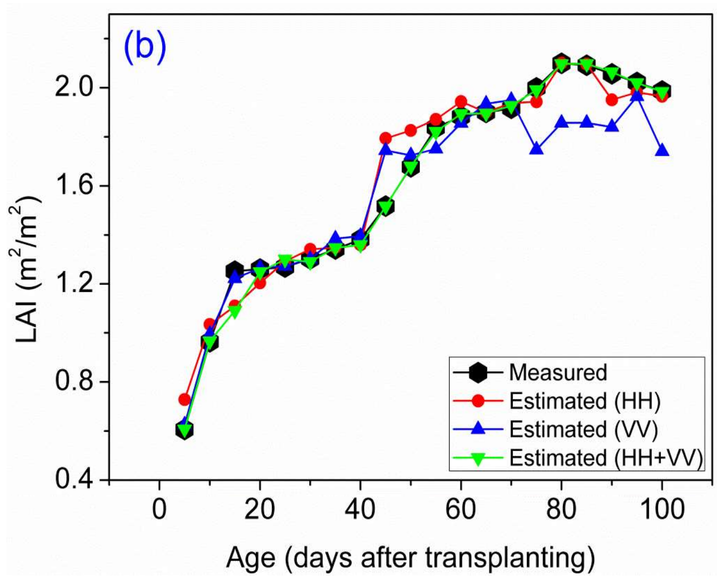
4.5.2 FEED FORWARD BACK PROPAGATION ARTIFICIAL NEURAL NETWORK (FFBPANN) FOR THE ESTIMATION OF RICE CROP VARIABLES

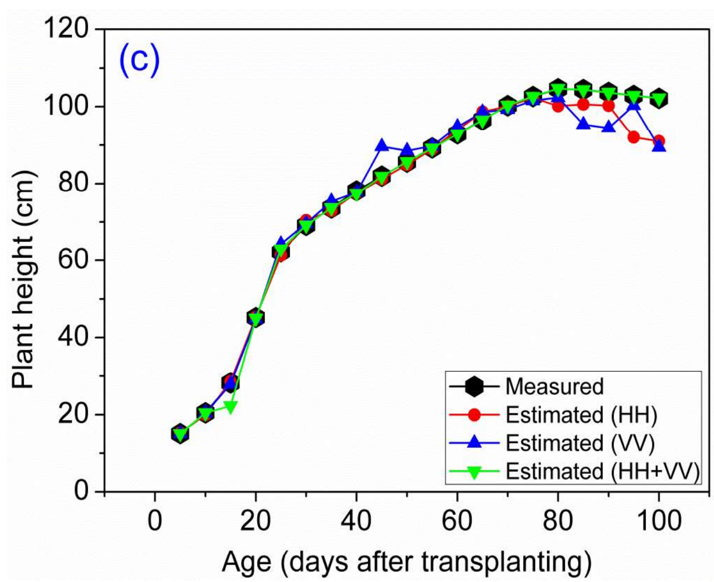
The performance of FFBPANN-I and FFBPANN-II model for the estimation of VWC, LAI, PH and SPAD value are shown in Figure 4.6 (a-d). The estimated values of rice crop variables were found very close to the observed values by both the FFBPANN models. However, the estimated values of rice crop variables by the FFBPANN-II model were found much closer to the observed values in comparison to the FFBPANN-I model.

The results of statistical analysis carried out to evaluate the performance of FFBPANN models is presented in Table 4.5. The statistical analysis was done between the observed value and the estimated value of rice crop variables by both FFBPANN models. The FFBPANN-I model was used to estimate the rice crop variables using single polarized data set (either HH- polarized data set or VV-polarized data set). In the case of FFBPANN-I model, the values of coefficient of determination (R^2) were found to be 0.986, 0.954, 0.986, 0.886 for crop variables VWC, LAI, PH, SPAD value, respectively at HH- polarization. For VV polarization, the values of R^2 were found to be 0.964, 0.919, 0.975, 0.810 for crop variables VWC, LAI, PH, SPAD value, respectively. Using the FFBPANN-II model, the values of R^2 were found to be 0.995, 0.968, 0.998, 0.993 for crop variables VWC, LAI, PH, SPAD value, respectively. The high values of R^2 indicate very good performance of both the FFBPANN models for the estimation of rice crop variables. However, the FFBPANN-II model trained with dual polarized data sets (HH- and VV-) provided better results than the FFBPANN-I model trained with single polarized data sets (HH- or VV-). The estimated values of rice crop variables by FFBPANN-I model were slightly scattered at the later growth stage than its initial stage of growth.

The bistatic scattering response depends on the orientation and structure of rice constituents with respect to polarization of incident wave. At the initial growth stages, the orientation and structure of rice constituents were uniform in comparison to later growth stages of the rice crop. At the later growth stages, the orientation of the leave and stems became randomly distributed over the rice crop bed. Thus, the single polarized data set is not adequate to acquire the additional information available due to polarimetric response of orientation and architecture of rice constituents. Therefore, it may be beneficial to use polarimetric data sets for the training of FFBPANN to achieve accurate estimation of the rice crop variables. The high correlation between the observed and estimated crop variables by the FFBPANN models indicates the potential of FFBPANN model for the accurate estimation of rice crop variables.




(b)
LAI (m^2/m^2)
2.0
1.6
1.2
0.8
0.4
0
20
40
60
80
100
Age (days after transplanting)
Measured
Estimated (HH)
Estimated (VV)
Estimated (HH+VV)


(c)
Plant height (cm)
120
100
80
60
40
20
0
0
20
40
60
80
100
Age (days after transplanting)
Measured
Estimated (HH)
Estimated (VV)
Estimated (HH+VV)

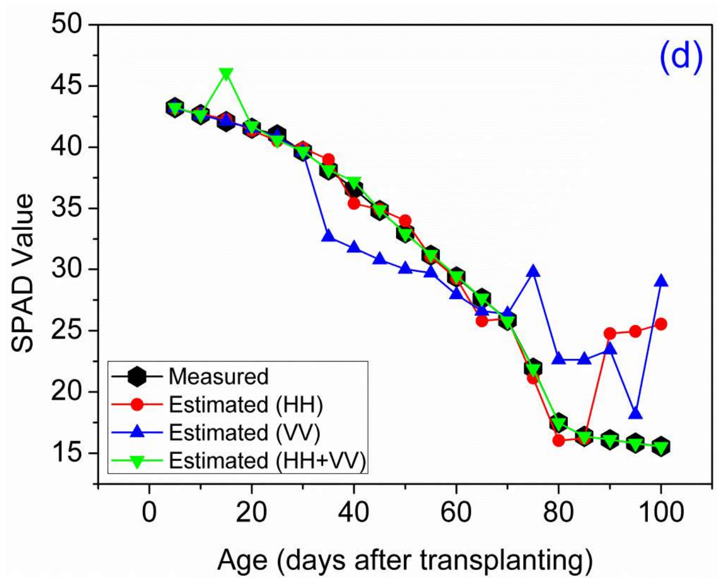


Figure 4.6 Performance of first FFBPANN models for the retrieval of rice crop variables for (a) VWC (b) LAI (c) PH (d) SPAD value with different combination of data sets

Table 4.5 Linear regression results between observed and FFBPANN estimated values of crop variables for three different data sets

Regression coefficient	HH- Polarization				VV- Polarization				Combined HH- and VV- polarization			
	VWC	LAI	PH	SPAD value	BM	LAI	PH	CC	VWC	LAI	PH	SPAD value
R	0.993	0.976	0.993	0.941	0.982	0.958	0.987	0.900	0.997	0.984	0.999	0.996
R^2	0.986	0.954	0.986	0.886	0.964	0.919	0.975	0.810	0.995	0.968	0.998	0.993
Adj_ R^2	0.985	0.951	0.985	0.880	0.962	0.914	0.974	0.800	0.995	0.962	0.998	0.992
SE	0.178	0.090	6.220	1.860	0.172	0.078	6.211	1.537	0.187	0.049	6.660	2.350
SEE	0.091	0.086	3.170	2.900	0.144	0.101	4.249	3.240	0.053	0.213	1.200	0.851
RMSE	0.118	0.091	3.860	3.650	0.157	0.133	4.603	4.740	0.057	0.037	1.340	0.912

4.6 CONCLUSIONS

The significant temporal and angular variations of bistatic scattering coefficient for the rice crop were observed at X-band. The high sensitivity of the HH- and VV- polarized bistatic scattering coefficients with the rice crop variables was observed at an incidence angle 30°. However, the HH- polarized bistatic scattering coefficients were found more sensitive in comparison to VV- polarized bistatic scattering coefficients with the rice crop variables at 30° incidence angle. The performances of both the developed FFBPANN models were found good for the estimation of rice crop variables. However, the performance of FFBPANN-II was found better in comparison to the FFBPANN-I model. Hence, the polarimetric data sets may be useful for the accurate estimation of rice crop variables using ANN.