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WHEAT CROP GROWTH PARAMETERS RETRIEVAL USING FULL POLARIMETRIC GROUND-BASED SCATTEROMETER DATA

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ABSTRACT

This article presents the utility of radar vegetation index (RVI), Pauli decomposition and full polarimetric data acquired, using a ground-based scatterometer to retrieve canopy height, leaf length and stem width of wheat crop. Polarimetric backscatter data at L and S bands at different incidence angles from 10^0 to 70^0 in steps of 5^0 was acquired over phenological stages of the wheat crop. In situ ground data from the field, including canopy height, leaf length and stem width, was collected to validate results. The RVI and Pauli decomposition components were computed, and their contribution to wheat parameter estimation was further explored using generalized regression neural network. Pauli decomposition has been utilized to investigate the performance of full polarimetric multitemporal scatterometer data for monitoring growth stages of wheat crop. Comparing observed and predicted canopy height, stem width, and leaf length retrieved from polarimetric data yielded root mean square error (RMSE) values varying from 1.327 to 0.014. The study revealed that the best retrieval results were obtained after combining backscattering values with RVI. This combination resulted in RMSE values of 0.560, 0.179 and 0.014 for canopy height, leaf length and stem width, respectively.

Keywords: *Ground Based Scatterometer (GBS), Canopy Height (CH), Radar Vegetation Index (RVI) and Generalized Regression Neural Network (GRNN).*

1. INTRODUCTION

Wheat is a staple food for most of the states in India. Remotely sensed estimates of biophysical parameters like canopy height (CH), leaf length (LL) and stem width (SW) are essential traits used to quantify crop yield in precision farming [1,2]. Among cereal crops, CH is a crucial indicator of crop health throughout the phenological stages [3]. Traditionally CH was determined manually in the field with the help of a ruler. However, manual measurements require much time and effort and are subject to errors. Therefore, efforts to develop a fast, reliable and robust method to estimate CH, LL and SW are needed, as they are the primary inputs in crop yield and condition models [4]. Microwave remote sensing data has a higher potential for regular monitoring of wheat crop conditions than optical sensing due to its unique qualities to acquire data in cloud cover regions, all weather conditions, night and day and its higher ability to penetrate canopies [5,6]. Ground based Scatterometers (GBS) are very valuable in measuring and analyzing vegetation scattering characteristics because of their easy operation and ability to provide uninterrupted crop monitoring using multi-polarization, multifrequency, and various incidence angle observations [7,8]. Various polarizations provide crucial information regarding the target. For crop parameter estimation and classification, priority will be given to polarization interacting more strongly with plant volume. VV is preferred while dealing with vertical canopy structure, for multiple scattering in vegetation, combining VV and VH provides good classification results [9] as compared to single polarization. Over the past few decades, researchers have widely used GBS to find solutions for many practical applications [10,11]. Yihyun Kim et al. used L, C and X bands backscatter for detecting soybean growth stages. The experimental study revealed that L-band HH polarization data is most appropriate for retrieving vegetation biophysical parameters [12]. Lei. He. et al. used a modified water cloud model for estimating biomass and found that wheat ears are essential for theoretical modelling as they affect the final yield

[13]. Yisok Oh et al. proposed utilizing a polarimetric ratio to estimate rice growth using GBS [14]. D.K. Gupta et al. set bistatic GBS and used feed forward back propagation neural network to retrieve rice growth parameters and found that a polarimetric dataset has a higher potential for training a neural network than single polarized data [15]. The vegetation parameters of several crops showed a high correlation with the backscattering coefficient in line with the angle of incidence, polarizations and frequency band [16- 19]. Y. Kim et al. proposed the radar vegetation index (RVI) application for monitoring crop growth. They concluded that RVI was found more beneficial and appropriate than primary polarimetric data because of its quality of being less susceptible to the influence of both incidence angle and environmental conditions [20,21]. Previous studies have used GBS to establish relationships between backscattering coefficients and crop growth variables however only few studies have focused on use of RVI to monitor vegetation parameters using GBS. Hence keeping above facts in view, this investigation aims to evaluate the utility of backscattering coefficient, RVI and Pauli decomposition to retrieve wheat growth variables using GBS. Pauli decomposition concept was adapted to split backscattering mechanisms into a single bounce scattering (α), double bounce scattering(β) and volume scattering (γ). The main objectives of the paper are 1. Combining backscattering coefficients, α, β, γ and RVI to retrieve CH, LL and SW of wheat crop using generalized regression neural network [GRNN] and 2. To investigate the suitability of backscattering coefficients and various full polarimetric data derived vegetation descriptors for estimating growth parameters of wheat.

The proposed experimental approach uses GBS and ground measurements to monitor wheat canopy over a phenological cycle. GBS full polarimetric L and S-bands observations at different incident angles have been utilized to examine wheat growth parameters. The paper is arranged as follows: Section II introduces data acquisition using GBS, field measurements and methodology, and the results of the finding are presented in the next Section, and in Section IV conclusion and future developments are discussed.

2. METHODS

The overall flow of proposed method is presented in figure 1. Following main steps are adopted in methodology for implementing proposed algorithm.

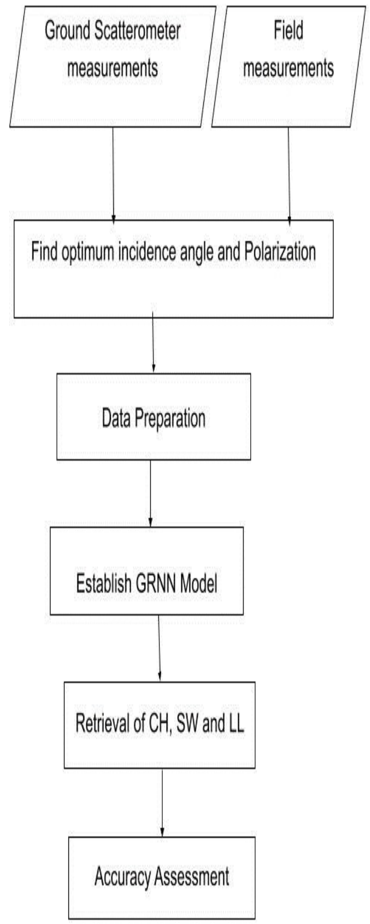

Figure 1 Flowchart for CH, SW and LL retrieval using GRNN

2.1 Data Acquisition

Data used in this study includes data acquired with the help of GBS and field measurements.

2.1.1 Experimental setup of Microwave Ground Scatterometer

A polarimetric scatterometer system based on step frequency continuous wave mode was installed on a portable wooden stand near a wheat field. The GBS setup comprises of L and S-band horn antennas having a gain of 20 dB and bandwidth of 1.9GHz, a vector network analyzer (VNA, 1GHz ~ 4 GHz) and a computer for data storage. Antennas were installed on a wooden platform to provide look angle variations from 10° to 70°. The look angle of the antenna was read using a circular scale with a pointer provided on the wooden stand. A total of five experimental acquisitions using GBS were taken over the wheat

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field in a study area at VV, VH, HV, and HH polarizations of L and S bands. A backscattering coefficient for L and S bands was computed using averages from the measurements obtained over the respective frequency bands. The study site is a wheat field covering approximately 7 acres located in Pusad, Yavatmal, India. The experiment was conducted from January 2022 to April 2022.

2.1.2 Field measurement

During the phenological cycle of the wheat crop, plant geometry parameters such as CH, LL and SW of the wheat crop were measured during each GBS data acquisition time. A wooden scale of two-meter length was utilized for the measurement of CH. Five sampling points in the wheat field were randomly chosen during each experiment to acquire representative data. The CH, LL and SW were measured by calculating the average of measurements of CH, LL and SW at five various locations in the study area.

2.2 Find optimum incidence angle and polarization

Regression analysis was used to estimate wheat crop CH, LL and SW to ascertain the GBS's ideal angle of incidence and polarization [22]. For regression analysis the independent parameters were the growth parameters, whereas the scattering coefficient was the dependent parameter. It was concluded that 30° angle of incidence and HV polarization were optimum sensor parameters to estimate wheat growth parameters at L and S–bands in our case.

2.3 Data preparation

To estimate wheat growth parameters the Pauli decomposition components, RVI with backscattering coefficients were utilized.

2.3.1 Pauli decomposition

The measured scattering matrix is described by a 2X2 matrix [S] with components S_{hh}, S_{hv}, S_{vh} and S_{vv}, which represents four combinations of the incident and scattered electric fields. The sent and received signals are represented in this matrix by the first and second subscripts, respectively (H horizontal and V vertical). Pauli decomposition was first expressed by Pottier [23]. Pauli decomposition technique is one of the most applied but intuitive technique used for separating full polarimetric data into α, β and γ [24] using equation 1 to 4.

$$[s] = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} = \alpha[s]_a + \beta[s]_b + \gamma[s]_c \quad (1)$$

Where

$$\alpha = \frac{S_{hh} + S_{vv}}{\sqrt{2}} \quad (2)$$

$$\beta = \frac{S_{hh} - S_{vv}}{\sqrt{2}} \quad (3)$$

$$\gamma = \sqrt{2S_{hv}} \quad (4)$$

Amalgamation of α, β and γ occurs in agricultural areas, the proportion that each of these scattering sources contributes to the total backscatter for a particular crop depends primarily on the growth stage of the crop. The backscatter is dependent on the canopy's structure, the plant's dielectric properties, the row alignment and planting density, and sensor configurations like incidence angle, polarization and frequency. As the crops grow from different phenological growth stages, there is variation in a plant's water content and structural attributes. These temporal variations can be used for crop identification and monitoring crops to assist in yield modelling [25]. The frequency and polarization of the incoming microwave are two variables that influence each scattering mechanism [26].

2.3.2 Radar vegetation index

RVI is most competent for utilizing time series observations for crop growth monitoring due to its less sensitivity towards variations in incidence angle and environmental conditions. The RVI is normalized to get an ideal range of values from 0 and 1, using measured linear scattering intensities from the cross and copolarization. Its value increases with an increase in vegetation cover.

$$RVI = \frac{8\sigma_{hv}}{\sigma_{hh} + \sigma_{vv} + 2\sigma_{hv}} \quad (5)$$

RVI is computed using equation 5, Where σ_{hv} represents cross-polarization backscattering cross section and σ_{hh}, and σ_{vv} represents co-polarization backscattering cross sections. For smooth bare surfaces, the value is almost zero. However, as vegetation grows, the value increases until it reaches its maximum at the peak growth stage [21].

The observed and calculated data sets, which include scattering coefficient, crop growth variables, RVI and Pauli decompositions, were interpolated into 90 data sets of the wheat crop at the 30^0 incidence angle for HV polarization. Interpolation was performed considering crop growth parameters as independent variables and backscattering coefficients as dependent variables [15]. In the dataset whole feature set was normalized in the 0 to 1 range utilizing maximum and minimum values of all features during the

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entire period. The interpolated datasets of wheat crops acquired during different growth stages were utilized for the training and testing GRNN models.

2.4 Generalized Regression neural network

Specht, in 1991 proposed GRNN for estimating continuous variables [27]. GRNN is a machine learning model mostly applied for function approximation to handle regression tasks. GRNN has shown great potential in remote sensing tasks, mostly in retrieval related applications. Previous research has found that the GRNN is more advantageous over BNPP in dealing with small sample sizes [28]. The architecture of GRNN is presented in figure 2.

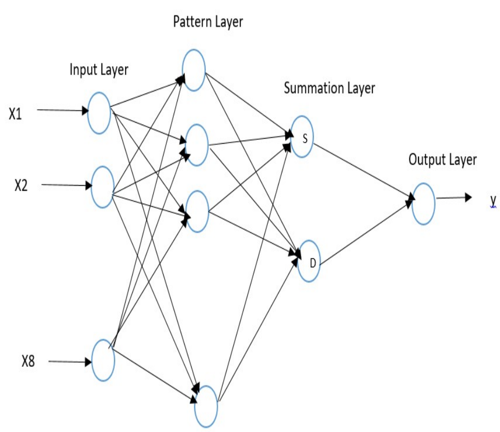

Figure2 GRNN architecture

Input layer, pattern layer, summation layer, and output layer are the four layers that make up the GRNN. The input is received by the first layer which is the input layer. The input layer is followed by the pattern layer which analyses the data in a way that makes it possible to remember the correlation between the input and output variables. As a result, there are exactly as many neurons in the pattern layer as in training samples. The pattern layer is connected to the summation layer, comprising of two types of summation neurons. Both weighted and unweighted outputs of the neurons in the pattern layer are combined using the summation neurons. The output layer's last neuron calculates the outputs of the summation layer to generate an estimated result. In our presented work, the GRNN model has eight inputs (backscattering coefficients VV, VH, HV, HH, α, β γ and RVI). In addition, the output layer had one node, the growth parameter (CH or LL or SW), to be retrieved. We have used the GRNN package integrated into the python software, setting the spread of the radial basis functions to 0.5. The GRNN design was chosen for this study because it is an iterative procedure-free one-pass learning algorithm with a highly parallel network.

2.5 Retrieval of CH, SW and LL

In this step wheat growth parameters are retrieved using the statistical relationship between growth parameters, radar backscatter (σ°), Pauli decomposition parameters and RVI using GRNN model.

2.6 Accuracy Assessment

The performance of retrieval algorithm was assessed using root mean squared error (RMSE).

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(GP_m - GP_o)^2} \qquad (6)$$

This metric is defined as Where GP_m is the estimated growth parameter, GP_0 is the original growth parameter.

3. RESULTS AND DISCUSSION

3.1 Pauli decomposition

A primary objective of the section was to explore the temporal progression of the three decomposition parameters throughout the vegetation season, from the beginning of January until the end of April. As the physical characteristics of crop change as the crop grows; therefore how these changes influence single bounce, double bounce and volume scattering was figured out. Figure 3 shows the wheat crop's tillering, stem emergence, milk stage and maturation stage during the experiment. Figure 4 shows the temporal variation of Pauli decomposition components of the backscattering coefficients for the two frequency bands. Single bounce scattering is the principal constituent over the entire evaluation period for both bands, and the Pauli decomposition component values were found to be the highest for the L-band. The double bounce component was maximum in March when the crops were fully grown. Double bounce became closest to volume scattering throughout the stem emergence stage. In the maturation stage, the difference between the two components was more prominent in wheat for the L and S band.

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Figure3 Field photographs of wheat crop

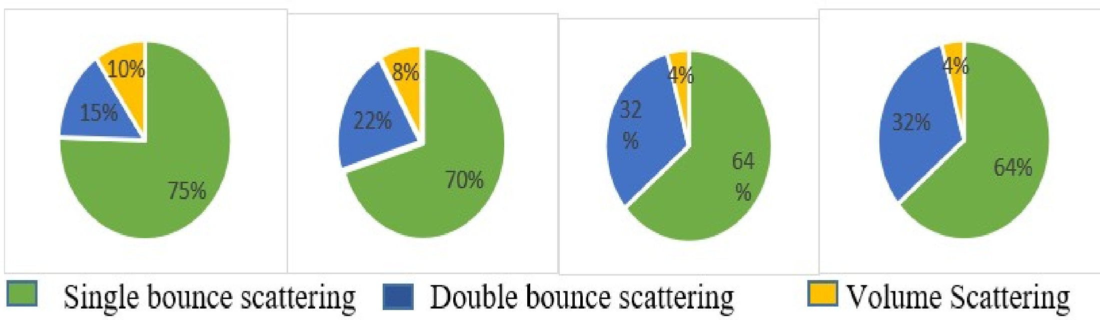

Figure4 Temporal variation of Pauli decomposition

A wheat canopy is primarily made up of tall stalks, and double bounce scattering is dominant in vertical structure compared to volume scattering mechanisms. In the early stage of wheat single bounce scattering is dominant due to bare soil present between wheat crops. Volume and double bounce scattering results in minor contributions to overall backscatter before crop emergence stage of the crop. Double bounce scattering increases as the crop grows, the contribution due to double bounce increases to 22% at crop emergence stage. Further, in March and April, double bounce scattering reaches a maximum of 32% due to the dense vertical wheat canopy, and volume scattering decreases to 4%. The results demonstrate that substantial modification occurs in the scattering mechanism when crops move from the progression of phenological stages. Observing these variations over the phenological crop cycle helps monitor crop development. Variation of scattering components in the GBS data can be utilized for the identification of crops, and the phenological cycle of crops and growth parameters also can be estimated from this information.

3.2 Radar vegetation index

Figure 5 shows the temporal pattern of RVI of the L and S band during the growth cycle. An evident change in RVI pattern is observed in the study area from January to April. The RVI value initially showed an increasing trend until March and then began to decline for the L and S bands indicating that with the growth of the crop and the

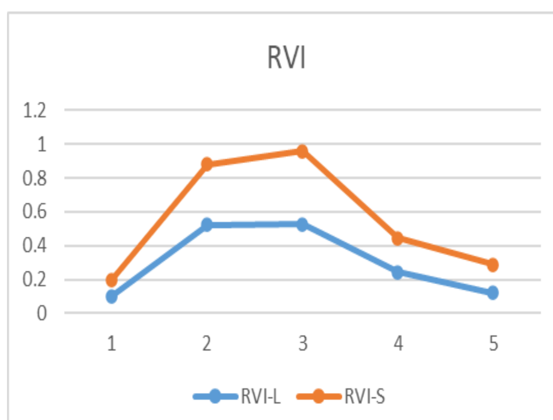

Figure 5. Temporal variation of L and S band RVI

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structure of wheat becomes more complex. The RVI of crop peaked in March and then decreased due to harvest. A comparison of the L and S band RVIs revealed that both bands showed recurring trends over time for wheat. L-band had the highest value and range of RVI compared to the S band. RVI is most appropriate for monitoring the amount of growth with the help of time series observations.

3.3 Retrieval of crop growth parameters

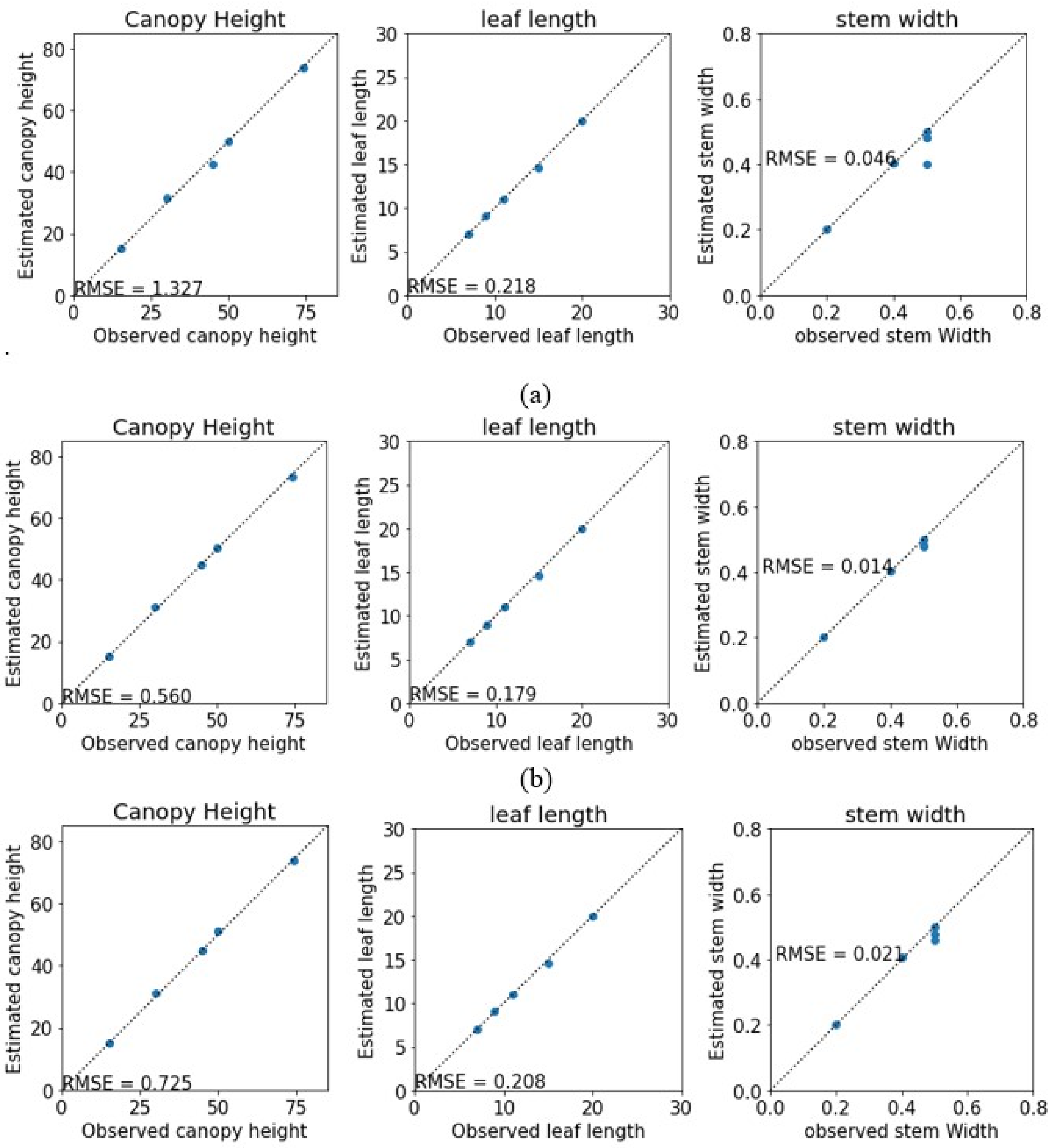
This section focusses on wheat growth parameters retrieval method based on the statistical relationship between growth parameters, radar backscatter (σ°), Pauli decomposition parameters and RVI. We performed a correlation analysis between the σ^0 and wheat crop growth variables to choose the ideal incidence angle and polarization at L and S bands for estimating growth related variables using GRNN. The maximum correlation coefficient between σ^0 and wheat crop growth variables was observed at 30° incidence angle for both bands utilized in the investigation. Polarimetric backscattering coefficient of wheat crop at 30° angle of incidence for L band at HV polarization were interpolated in 91 data sets which was further divided into 63 and 28 data sets for training and testing respectively for GRNN model. The dataset whole feature set was normalized in 0 to 1 range utilizing maximum and minimum values of all features during the entire period. The datasets were randomly subdivided into 70 to 30 ratio for training and testing.

In order to explore application of RVI for growth parameter estimation GRNN model was systematically tested for three sets of inputs and that are 1. Backscattering Coefficient and 2. Backscattering coefficient + RVI 3. Backscattering Coefficients+ α, β, γ. The obtained results for all three data combinations are presented in Table 1. The comparison between predicted and observed CH yielded a RMSE of 1.3227 using backscattering coefficient, 0.725 using backscattering coefficient and α, β, γ and 0.560 using RVI and backscattering coefficient. In case of LL RMSE of 0.218 using backscattering coefficient, 0.179 using backscattering coefficient and RVI and 0.208 using backscattering coefficient and α, β, γ. In case of SW RMSE of 0.046 using backscattering coefficient,0.014 using backscattering coefficient and RVI and 0.021 using backscattering coefficient and α, β, γ. Figure 6 shows retrieved CH, LL and SW versus situ measurements for all three data combination. From obtained results we conclude that the most accurate estimation of canopy height, leaf length and stem width was retrieved using RVI and backscattering coefficient.

In [12] comparison between predicted and CH resulted in RMSE of 1.34, the proposed method gave RMSE of 0.560 the increment in accuracy was obtained since RVI was added. These results clearly demonstrated the potential of RVI for estimating vegetation canopies parameters. RVI performed better due to its quality of being less susceptible to the impact of both incidence angle and environmental conditions.

Table1: RMSE and MSE for CH, LL and SW for each input

Data	Canopy height		Leaf Length		Stem Width	
	RMSE	MSE	RMSE	MSE	RMSE	MSE
Backscaterring coefficient	1.327	1.76	0.218	0.047	0.046	0.002
Backscaterring coefficient+ RVI	0.560	0.313	0.179	0.032	0.014	0.0002
Backscaterring coefficients + α, β, γ	0.725	0.525	0.208	0.043	0.021	0.00043



(c)

Figure 6. Retrieved ground parameters versus in situ measurements for (a) Backscaterring coefficients and (b) Backscaterring coefficients and RVI (c) Backscaterring coefficients + α,β,γ

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4. CONCLUSION AND FUTURE SCOPE

Goal of this work was to develop and evaluate a new approach for retrieval of growth parameters over wheat crops based on full polarimetric scatterometer data. The work was based on GBS and field measurement data of growth parameters over wheat crop. Pauli decomposition and crop growth data RVI variation were noted over wheat growth cycles. The wheat crop variables were observed to increase more quickly at early phases of the growth in comparison to the later growth stages. The results of three different dataset combinations, one based on the backscattering coefficient, other based on backscattering and RVI and last on backscattering coefficient and Pauli parameters for wheat parameters estimation, were compared and discussed. All growth parameters were estimated well using RVI and backscattering coefficient with RMSE above 0.560, 0.179 and 0.014. As per the results obtained RVI proved to be the best parameter for growth parameter estimation. Further investigations will be focused on the combination of parameters and their effects on crop classification.

REFERENCES:

[1] L. K. Sharma, H. Bu, D. W. Franzen, and A. Denton, "Use of corn height measured with an acoustic sensor improves yield estimation with ground based active optical sensors," *Comput. Electron. Agriculture*, vol. 124,pp. 254–262, 2016.

[2] S. Chauhan, H. S. Srivastava and P. Patel, "Crop Height Estimation Using RISAT-1 Hybrid-Polarized Synthetic Aperture Radar Data," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 12, no. 8, pp. 2928-2933, Aug. 2019, doi: 10.1109/JSTARS.2019.2919604.

[3] J. M. Lopez-Sanchez, I. Hajnsek, and J. D. Ballester-Berman, "First demonstration of agriculture height retrieval with PolInSAR airborne data," *IEEE Geosci. Remote Sens. Lett.*, vol. 9, no. 2, pp. 242–246, Mar.2012.

[4] N. Jamil, G. Kootstra, and L. Kooistra, "Evaluation of individual plant growth estimation in an intercropping field with UAV imagery," *Agriculture*, vol. 12, no. 1, p. 102, 2022.

[5] H. Srivastava, K. Saini and T. Pant, "A Time Series Approach for Wheat Crop Harvest Detection using Multispectral Data," *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 2021, pp.6777-6780, doi:10.1109/IGARSS47720.2021.9554017.

[6] T. Le Toan, H. Laur, E. Mougin and A. Lopes, "Multitemporal and dual-polarization observations of agricultural vegetation covers by X-band SAR images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 27, no. 6, pp. 709-718, Nov. 1989, doi: 10.1109/TGRS.1989.1398243.

[7] Y. Kim et al., "Estimating wheat growth for radar vegetation indices," 2013 IEEE International Geoscience and Remote Sensing Symposium - IGARSS, 2013, pp. 3219-3222, doi: 10.1109/IGARSS.2013.6723512.

[8] Desai, G., Gaikwad, A. (2021). The Ground Based Scatterometer for Agriculture Applications. In: Abraham, A., Sasaki, H., Rios, R., Gandhi, N., Singh, U., Ma, K. (eds) Innovations in Bio-Inspired Computing and Applications. IBICA 2020. Advances in Intelligent Systems and Computing, vol 1372. Springer, Cham.

[9] Lin YC, Sarabandi K. A Monte Carlo coherent scattering model for forest canopies using fractal-generated trees. IEEE Transactions on Geoscience and Remote Sensing. 1999; 37:440-451.

[10] Mittal, Vikas, L. M. Saini, and D. Singh. "A study of PDF based approach to classify full polarimetric radar data." In *2015 National Conference on Recent Advances in Electronics & Computer Engineering (RAECE)*, pp. 324-327. IEEE, 2015.

[11] Agarwal, Smriti, and Dharmendra Singh. "Non-invasive multilayer dielectric material thickness measurement using V band millimeter wave radar." In *2016 Asia-Pacific Microwave Conference (APMC)*, pp. 1-4. IEEE, 2016.

[12]Y. Kim, T. Jackson, R. Bindlish, H. Lee, and S. Hong, "Monitoring soybean growth using L-, C-, and X-band scatterometer data," Int. J. Remote Sens., vol. 34, no. 11, pp. 4069–4082, Jun. 2013.

[13] L. He, L. Tong, Y. Li, Y. Chen, L. Tan, and C. Guo, "Polarimetric analysis of radar backscatter from ground-based scatterometers and wheat biomass monitoring with advanced synthetic aperture radar images," *Journal of Applied Remote Sensing*, vol. 10, no. 2, p. 026008, 2016.

[14] Y. Oh, S. -Y. Hong, Y. Kim, J. -Y. Hong and Y. -H. Kim, "Polarimetric Backscattering

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Coefficients of Flooded Rice Fields at L- and C-Bands: Measurements, Modeling, and Data Analysis," in IEEE Transactions on Geoscience and Remote Sensing, vol. 47, no. 8, pp. 2714-2721, Aug. 2009, doi: 10.1109/TGRS.2009.2014053.

[15] D. K. Gupta, P. Kumar, V. N. Mishra, R. Prasad, P. K. S. Dikshit, S. B. Dwivedi, A. Ohri, R. S. Singh, and V. Srivastava, "Bistatic measurements for the estimation of rice crop variables using artificial neural network," *Advances in Space Research*, vol. 55, no. 6, pp. 1613–1623, 2015.

[16] M. Jia, L. Tong, Y. Chen and J. Gao, "Multi-temporal radar backscattering measurement of wheat fields and their relationship with biological variables," 2012 IEEE International Geoscience and Remote Sensing Symposium, 2012, pp. 4590-4593, doi: 10.1109/IGARSS.2012.6350446.

[17] Q. Sun et al., "S-band backscattering analysis of wheat using tower-based scatterometer," 2012 IEEE International Geoscience and Remote Sensing Symposium, 2012, pp. 4621-4624, doi: 10.1109/IGARSS.2012.6350436.

[18] K.-S. Lim, V. C. Koo, and H.-T. Ewe, "Multi-angular scatterometer measurements for various stages of rice growth," *Progress In Electromagnetics Research*, vol. 83, pp. 385–396, 2008.

[19] K.-S. Lim, V. C. Koo, and H.-T. Ewe, "Multi-angular scatterometer measurements for various stages of rice growth," *Progress In Electromagnetics Research*, vol. 83, pp. 385–396, 2008.

[20] Y. Kim and J. J. van Zyl, "A Time-Series Approach to Estimate Soil Moisture Using Polarimetric Radar Data," in IEEE Transactions on Geoscience and Remote Sensing, vol. 47, no. 8, pp. 2519-2527, Aug. 2009, doi: 10.1109/TGRS.2009.2014944.

[21] Y. Kim, T. Jackson, R. Bindlish, S. Hong, G. Jung and K. Lee, "Retrieval of Wheat Growth Parameters With Radar Vegetation Indices," in IEEE Geoscience and Remote Sensing Letters, vol. 11, no. 4, pp. 808-812, April 2014, doi: 10.1109/LGRS.2013.2279255.

[22] Prakash, R., Singh, D. and Singh, O.P., 2016. Multi-incident angle approach to retrieve soil parameters for specular scattering. *IET Radar, Sonar & Navigation*, *10*(3), pp.560-568.

[23] Kim, Y. H., S. Y. Hong, and H. Y. Lee. 2009. "Estimation of Paddy Rice Growth Parameters UsingL, C, X-Bands Polarimetric Scatterometer." Korean Journal of Remote Sensing 25: 31–44.

[24] Pooja Mishra Dharmendra Singh Yoshio Yamaguchi , "Land Cover Classification of Palsar Images by Knowledge Based Decision Tree Classifier and Supervised Classifiers Based on SAR Observables," *Progress In Electromagnetics Research B*, Vol. 30, 47-70, 2011.

[25] C. Liu, J. Shang, P. W. Vachon and H. McNairn, "Multiyear Crop Monitoring Using Polarimetric RADARSAT-2 Data," in IEEE Transactions on Geoscience and Remote Sensing, vol. 51, no. 4, pp. 2227-2240, April 2013, doi: 10.1109/TGRS.2012.2208649.

[26] Y. Kim, H. Lee and S. Hong, "Continuous Monitoring of Rice Growth With a Stable Ground-Based Scatterometer System," in IEEE Geoscience and Remote Sensing Letters, vol. 10, no. 4, pp. 831-835, July 2013, doi: 10.1109/LGRS.2012.2225595.

[27] D. F. Specht, "A general regression neural network," in IEEE Transactions on Neural Networks, vol. 2, no. 6, pp. 568-576, Nov. 1991, doi: 10.1109/72.97934.

[28] Y. Cui, X. Chen, W. Xiong, L. He, F. Lv, W. Fan, Z. Luo, and Y. Hong, "A soil moisture spatial and temporal resolution improving algorithm based on multi-source remote sensing data and GRNN model," *Remote Sensing*, vol. 12, no. 3, p. 455, 2020.