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Agricultural crop growth biophysical parameters estimation by machine learning using microwave satellite data

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Abstract

Agriculture sector is the most significant for the Indian economy. So, it becomes necessary to estimate agricultural crop growth biophysical parameters for the proper crop monitoring and forecasting of the crop yield. The objectives of the research are estimation and comparison of wheat crop biophysical parameters using Sentinel-1A images by linear kernel based support vector regression (SVR) model, radial basis function based artificial neural network regression (ANNR) machine learning model and linear regression (LR) model. The ground samples of wheat crop growth biophysical parameters like as leaf area index (LAI), plant height (PH), fresh biomass (FB), dry biomass (DB), and vegetation water content (VWC) were collected during 8 January 2015 to 29 April 2015. The estimated results are statistically analysed and compared by coefficient of determination (R^2), Nash Sutcliffe efficiency (NSE), %bias and by the analysis of root mean square error (RMSE). Overall good results such as R^2 = 0.919, %bias = 1.153, NSE = 0.925 and RMSE = 0.661 values were found for the estimation of VWC using ANNR model. Whereas, LR model performed poorly for the PH estimation with the R^2 = 0.662, %bias = 5.638, NSE = 0.627 and RMSE = 18.347 values at C-band. The SVR and ANNR models are found more suitable for wheat crop biophysical parameters estimation in compare to the LR modeling approach. The outcomes of the present study by different models may offer the valuable information for accurate monitoring of multiple crops in future for better crop production.

Keywords: Sentinel-1A, SVR, ANNR, LR, biophysical parameters.

Introduction

Balancing national, regional and global foodstuff on increasing demand of rising population is a big challenge. Observing crop growth and production estimates using remotely sensed satellites can make an involvement to monitor food security at the regional to global scales[1]. Wheat crop is the major requirement for the livelihood of human being. Monitoring of wheat crop is a particular significance in India; globally it is the important food source. Space borne remote sensing has a vital role for discrimination and monitoring of crops due to its capability to provide perpetual coverage over larger areas. So many research studies have proven that optical satellite imagery can accurately discriminate crop types[2,3]. However, cloud cover in the optical remote sensing impedes during mapping and monitoring of diverse crop[4,5]. Synthetic Aperture Radars (SARs) are able for the observation in any weather or day/night conditions for the wide range of agricultural crop applications. These sensors are particularly useful in India as well as other tropical regions in the world where major number of crops are grown in rainy or cloudy months[6-8]. SAR satellite imagery applications for the estimation of crop growth biophysical parameters are challenging for the scattering geometry of crop which govern the microwave signal interaction with the crop/vegetation[6]. Backscattering by the microwave satellite for the wheat crop as a function of wheat crop growth is crucial for the expansion of consistent and robust models to estimate the crop biophysical parameters.

The crop growth variables like as vegetation water content (VWC), plant height (PH), leaf area index (LAI), and biomass are dependent on microwave frequency as well as polarizations, found correlated with the microwave backscattering values[9-13]. Picard G. et al.[14] have found strong relations with the LAI and FB at an angle of incidence 40° for wheat crop at C-band. Inoue, Y. et al.[15] utilized X-, C-, L-, Ku-, and Ka- bands for rice crop and found that C-band backscattering (for HH- and HV-polarization an angle of incidence 25° and for HV-polarization angle of incidence 35°) has shown the maximum correlation with the LAI parameter. However, Ku-band with different incidence angles and polarizations for LAI has shown good relationship with HH at 30° for corn, wheat and sorghum crops[16]. The sensitivity of VWC crop growth parameter was observed higher in comparison to the fresh biomass (FB) of wheat crop using VV-polarization at C-band[13]. The differences in the outcomes may be because of variations in crop structure, crop types, system parameters and weather conditions.

The proficiency of support vector machine has been shown for the classification studies[7,17]. This model was extended for the regression called SVR model which became prevalent in the past some years for monitoring of crop biophysical parameters. SVR model has given away his strength to noise even with the limited sample data[18-20]. Good agreement between observed and retrieved LAI was found using multi-angle imaging spectroradiometer by SVR model[19]. The efficiency of ANN model has been verified for the discrimination of crop types [21, 22]. Good results were found for the estimation of rice[23]; kidney bean[24], spinach[25], soil moisture and lady finger[26] crops. The radial basis function ANNR has shown better response in comparison to general regression neural network (GRNN) for the estimation of lady finger crop variables[27]. However, GRNN was found better predictor of potato crop biophysical parameters and yield than the radial basis function ANNR model[28].

This study inspected the potential of microwave data for the estimation of wheat crop biophysical parameters by linear kernel based SVR, radial basis function ANNR and LR models. This work also presents the applicability of SVR and ANNR models as an estimator could be useful to estimate the crop growth parameters of other crops. Sentinel-1A SAR data has resolved the complications related to the cost of imagery. Investigations have shown the usefulness of using Sentinel-1A data. Only some studies have been reported for the agricultural study purpose using Sentinel-1A SAR data[29-31]. The present investigation offers useful information that can be used to monitor the spatial distribution and monitoring of different crops in other regions worldwide. The current study have shown the C-band observations can be use for accurate estimation of LAI, VWC, FB, DB and PH at other C-band satellite data.

Materials and methods

Ground data collection: The Varanasi district is adopted as a study area situated in Uttar Pradesh, India. The major crop area was covered by wheat in this season (November 2014 to April 2015). The area is flat/a little undulated with an altitude of 81m. The research area has the centre latitude 25°17′51″N and longitude 82°56′36″E. The wheat crop fields used in present study were sown in the month of November and December 2014 and harvested in the month of April and May 2015. The selected area for the present study is shown by Figure-1.

The wheat crop biophysical parameters were observed at the different locations in the field during 8 January 2015 to 29 April 2015. LAI was measured at the different locations within the field using LAI-2200C Plant Canopy Analyzer. For the estimation of biomass, the samples of wheat plants of $1x1m^2$ area were collected at the diverse locations in study area. The plants (leaves and stalks) of winter wheat crop were dried in an oven at 105^0C for 20h. Collected samples were weighted by digital weighing machine before and after drying to work out the weight per m^2 of wheat crop for the computation of its FB and DB. VWC of the wheat crop was observed after subtracting DB from FB collected samples. PH measurements were done manually by tape measurement. Average values of collected samples of VWC, FB, LAI, DB and PH of five different dates with VV-polarization at C-band were used to estimate wheat crop biophysical parameters.

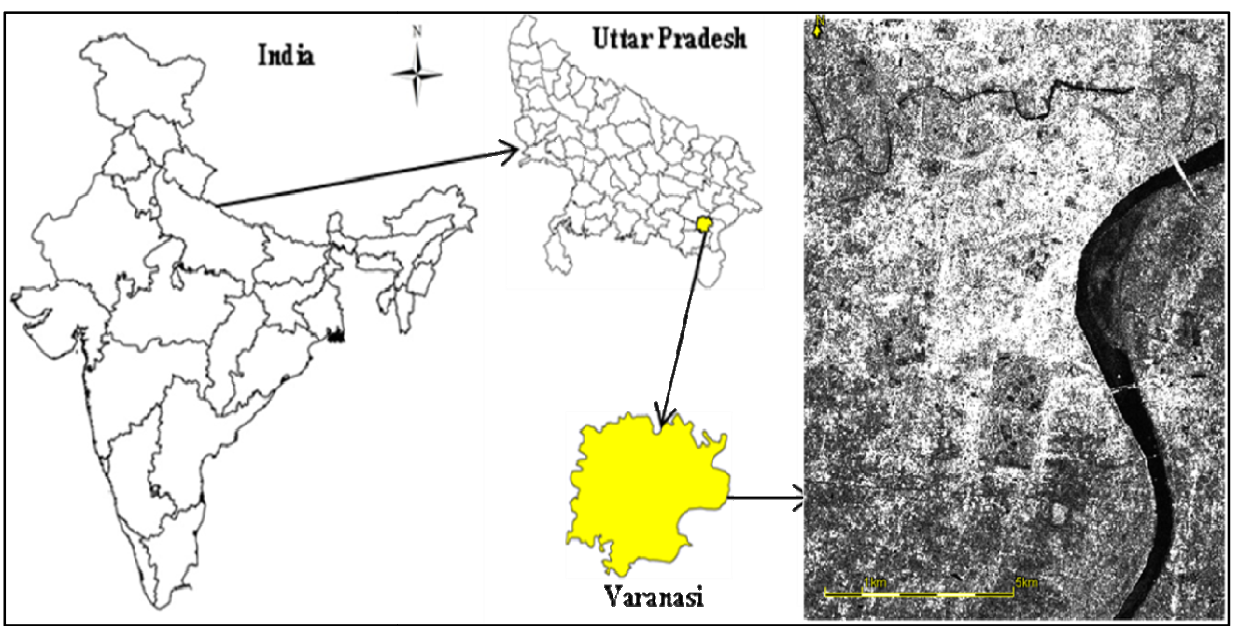

Figure-1: Research area is shown by the Sentinel-1A satellite imagery.

Satellite data processing and analysis: Sentinel-1A data of five different dates 8 January, 25 February, 05 March, 21 March and 29 April 2015 were acquired in the interferometric wide (IW) mode at VV-polarization to derive biophysical information in the wheat crop area. The datasets were of ascending and descending passes with ground range detected (GRD) level 1 product type having spatial resolution 20m.

Wheat crop biophysical parameters such as LAI, VWC, FB, DB and PH were investigated for estimation of crop growth to improve the production of crop. The backscatter relating to the wheat crop biophysical parameters were investigated using C-band data in Varanasi, India. Different polarizations of the microwaves were found to be sensitive to the parameters like shape, size and target orientation of scattering elements[26]. The Sentinel-1A data was processed using SNAP software mainly Sentinel-1 toolbox downloaded from website.

Linear kernel based support vector regression modelling: Support vector machine model was applied for the classification studies in the earlier days. However it was first introduced by Vapnik V. et al.[32] for the regression problems. The SVR model explains linear regression in feature space associating ε-insensitive loss function in analysis. Different types of kernel functions are like linear, radial basis, polynomial and sigmoid function kernel. In the present study linear kernel was used in the SVR modeling for the wheat crop biophysical parameters estimation. SVR tries to minimize the model complication by decreasing $\|w\|^2$ [18,32]. SVR can be explained mathematically as:

$$Min \frac{1}{2}\|w\|^2 + C \sum_{i=1}^{N}(\xi_i + \xi_i^*) \quad (1)$$

Subject to

$$w^T\phi(x_i) - y_i \ \varepsilon + \xi_i \quad (2)$$

$$y_i - w^T\phi(x_i) \le \varepsilon + \xi_i^* \quad (3)$$

$$\xi_i, \xi_i^* \ge 0, \quad (4)$$

where w is the weighting vector and the dimension of w is same as $\phi(w)$. C is the penalty parameter, ξ_i and ξ_i^* are known as slack variables; $i = 1 \ldots\ldots N$; N is training data numbers. Here ϕ is the kernel function, x_i *and* y_i are vectors applied in the training method[32,33].

Radial basis function based artificial neural network regression modelling: Radial basis function ANNR is one of the robust machine learning techniques to estimate crop growth parameters. This model is widely used for the non-linear datasets due to its high learning capability. The ANNR model has three layers as input, hidden and an output layer[28]. This ANNR model uses Gaussian activation function to compute output of hidden layer neurons[34]. The Gaussian function is mathematically defined as:

$$f(x) = \exp(-x^2) \quad (5)$$

After initializing weights in the input layer of the network the designed output of m^{th} node in output layer of system/network for nth sample is described by the equation as:

$$y_{mn} = \sum_{i=1}^{H} w_{im} v_i(x_i) + w_0 \quad (6)$$

where y_{mn} is output of m^{th} node in output layer of network for nth sample. H is number of hidden layers node and w_{im} is weight between i^{th} radial basis function unit and m^{th} output node. $v_i(x_i)$ is the output of i^{th} unit in hidden layer however w_o is biasing at the m^{th} output node[35,36].

Linear regression modelling: The LR modelled data via linear predictor function and unidentified parameters of model. One variable is considered as an independent variable (x_i), and the other is considered as a dependent variable (y_i)[37]. LR model can be defined mathematically as:

$$y_i = a + bx_i \quad (7)$$

where $i=1 \ldots\ldots\ldots\ldots n$. a and b are intercepts and slope values, respectively.

Performance indicators: The performance indicators such as %bias, Nash Sutcliffe Efficiency (NSE) and RMSE were evaluated to estimate crop biophysical parameters.

The value of %bias indicates deviation of the estimated values from the observed values[38]. %bias can be represented mathematically by the equation as:

$$\%bias = 100 * \left[\frac{\sum_{i=1}^{n}(y_i - x_i)}{\sum_{i=1}^{n} x_i}\right] \quad (8)$$

The NSE is also used for the evaluation of the models[39]. The NSE indicator is depending on sum of square of difference among estimated and observed samples normalized by variance of observed samples. NSE performance indicator can mathematically be written by the equation as:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2} \quad (9)$$

The RMSE is applied to evaluate the prospective of models to estimate different crop growth parameters[37,38,40]. It can be represented mathematically as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad (10)$$

where x_i, y_i and n are observed, estimated values of the parameters and number of observations, respectively.

Results and discussions

In the present study wheat crop biophysical parameters were estimated by the linear kernel SVR, radial basis function ANNR and LR models using Sentinel-1A data and compared with each other. 73 samples were used to train the models and 39 samples were applied to test the models to estimate wheat crop variables. To represent the results of the crop biophysical parameters graphically the 1:1 line linking observed and estimated VWC, LAI, FB, PH and DB values were fixed and R^2, %bias, NSE, and RMSE values were computed. The results were analysed and compared by using the performance indicators such as R^2, NSE, %bias and RMSE values. In all five biophysical parameters it was analysed that the observed values were not found closer to the estimated values through the models at the ripening stage of the crop. It may be the indication of the wheat crop biophysical parameters was found less interacted with the backscattering values of the Sentinel-1A. The higher values of R^2 and NSE however lower values of %bias and RMSE indicate a good analytical model performance. Table-1 summarizes the results obtained for wheat crop variables using R^2, %bias, NSE and RMSE by the linear kernel based SVR, radial basis function based ANNR and LR models.

The estimated values of LAI using SVR (R^2 = 0.867, NSE = 0.858 and RMSE = 0.481) and ANNR (R^2 = 0.872, NSE = 0.874 and RMSE = 0.494) models were found comparable. However, results of LAI obtained by the LR model such as R^2 = 0.758, %bias = 3.492, NSE = 0.739 and RMSE = 0.746 were found lower in compare to the SVR and ANNR models. Though the results obtained by the LR model were found good in comparison to the results obtained by the LR model for the FB, DB and PH. The overestimation at the tillering stage whereas the underestimation at ripening stage was observed for the LAI estimation using LR model. LAI crop growth parameter was found the second best estimated parameter after the VWC crop growth parameter. The R^2 = 0.867 by SVR and R^2 = 0.872 by ANNR models for the estimation of LAI were found slightly less in compare to the R^2 = 0.906 value by SVR and R^2 = 0.919 using ANNR for the estimation of VWC. However estimated results for the LAI by linear SVR, radial basis function ANNR and LR models were found better in compare to the DB, FB, and PH parameters. Figure 2 show the graphical representation between observed and estimated LAI of the wheat crop by linear kernel based SVR, radial basis function ANNR and LR models.

Table-1: The estimated results of the wheat crop biophysical parameters by R^2, %bias, NSE and RMSE by the linear kernel based SVR, radial basis function based ANNR and LR models.

Crop parameters	Models	R^2	%bias	NSE	RMSE
LAI (m^2/m^2)	SVR	0.867	1.529	0.858	0.481
	ANNR	0.872	1.397	0.874	0.494
	LR	0.758	3.492	0.739	0.746
VWC (kg/m^2)	SVR	0.906	1.205	0.893	0.688
	ANNR	0.919	1.153	0.925	0.661
	LR	0.845	1.927	0.847	0.824
FB (kg/m^2)	SVR	0.810	-2.118	0.815	1.662
	ANNR	0.813	2.723	0.801	1.619
	LR	0.726	3.196	0.704	2.568
DB (kg/m^2)	SVR	0.756	-2.501	0.737	0.944
	ANNR	0.742	2.472	0.741	0.811
	LR	0.681	4.205	0.658	1.324
PH (cm)	SVR	0.719	-2.781	0.664	16.183
	ANNR	0.704	3.456	0.652	14.490
	LR	0.662	5.638	0.627	18.347

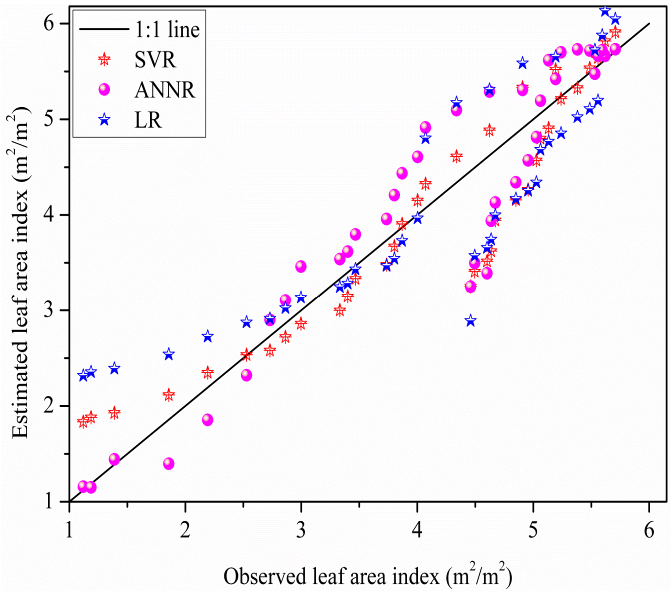

Figure-2: Graphical representation between observed and estimated leaf area index values of wheat crop by linear kernel based SVR, radial basis function based ANNR and LR models.

Overall highest R^2 = 0.919 value, %bias = 1.153, NSE = 0.925 and RMSE = 0.661 were found for VWC by radial basis function ANNR model in compare with LAI, DB, FB, and PH crop growth parameters. However good R^2 = 0.906, %bias = 1.205, NSE = 0.893 and RMSE = 0.688 for VWC were also found by linear kernel based SVR. The linear kernel based SVR model results are indicative of the promising characteristics of SVR model. Good simplification capability and the strength to noise having few samples are the prime capability of the SVR model [41]. However, SVR can offer results poorly when features are much larger than samples used in the estimation by the model. Kernel based SVR has shown sensitivity to the over-fitting in the estimation process [42]. The ANNR model has the high learning capability of large datasets accurately. The estimated results were found close to 1:1 line at the tillering, jointing, heading and ripening stages using linear kernel based SVR and radial basis function based ANNR models. Good relation between observed and estimated values at these stages indicates the better performance by using linear kernel based SVR and radial basis function based ANNR to estimate VWC. However some overrated VWC values were observed at initial stages like tillering and booting using LR model. Figure 3 show the graphical representation between observed and estimated VWC of the wheat crop by linear kernel based SVR, radial basis function ANNR and LR models.

The R^2 = 0.810, %bias = -2.118, NSE = 0.815 and RMSE = 1.662 using SVR and R^2 = 0.813, %bias = 2.723, NSE = 0.801 and RMSE = 1.619 using ANNR models were found for the estimation of FB. Nearly same R^2 values were found using SVR and ANNR for the estimation of FB; however ANNR has slightly performed better in comparison to SVR model. The LR model estimated values for the FB were found better than the DB and PH values however the results of LR model for the FB were found less in comparison to the results of LAI and VWC crop growth parameter. The estimated results for the FB by the SVR and ANNR were also found good; however these results were found somehow less in compare to the results obtained by SVR and ANNR for the LAI and VWC parameters. The over estimation was found at tillering and booting and underestimation was observed at ripening phase via LR model. However, the ANNR model has shown almost overestimation at every stage except later stage of ripening. Figure-4 show the graphical representation between observed and estimated FB of the wheat crop by linear kernel based SVR, radial basis function ANNR and LR models.

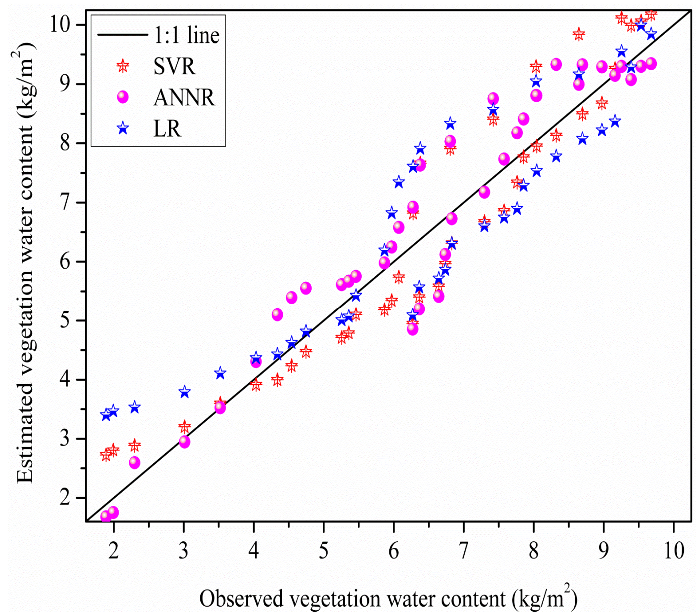

Figure-3: Graphical representation between observed and estimated vegetation water content values of the wheat crop by linear kernel based SVR, radial basis function based ANNR and LR models.

In the DB estimation, R^2 = 0.756, %bias = -2.501, NSE = 0.737 and RMSE = 0.944 values were found using SVR whereas R^2 = 0.742, %bias = 2.472, NSE = 0.741 and RMSE = 0.811 were found using ANNR model. However the estimated values using LR model were found less for the DB in compare to SVR and ANNR model. The estimated DB values were bring into being close to 1:1 line at almost every stage using SVR however at the ripening stage values were highly underestimated. Overestimated values were found almost every stage except the ripening stage using ANNR and LR models. At the ripening stage the values were highly underestimated using all three models. High underestimated values at the later stage indicate that the values of backscattering and DB were found less interacted at the ripening stage of crop. Figure-5 show the graphical representation between observed and estimated DB of the wheat crop by linear kernel based SVR, radial basis function ANNR and LR models.

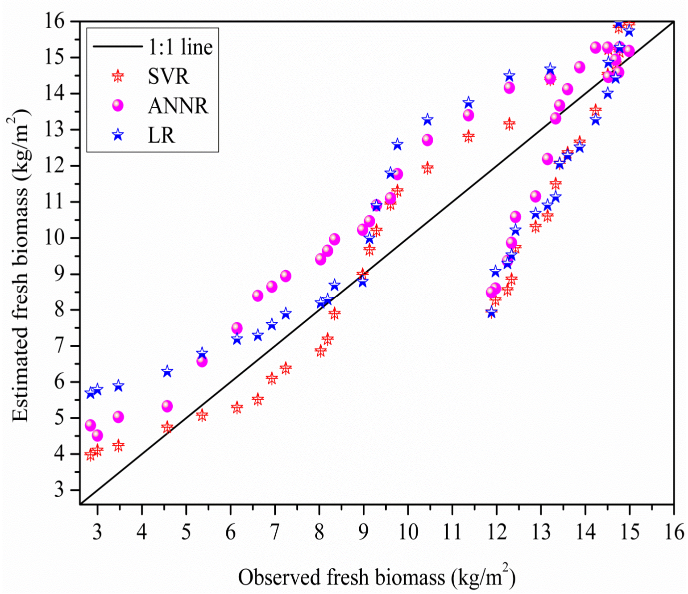

Figure-4: Graphical representation between observed and estimated fresh biomass of wheat crop by linear kernel based SVR, radial basis function based ANNR and LR models.

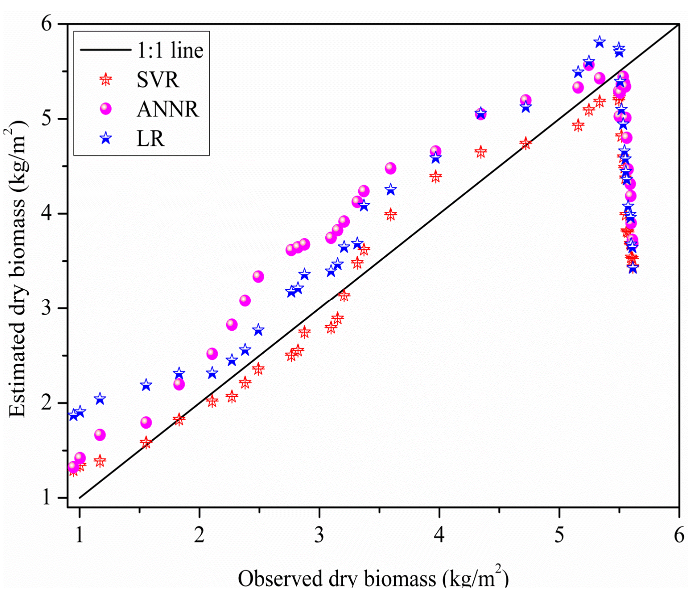

Figure-5: Graphical representation between observed and estimated dry biomass values of wheat crop by linear kernel based SVR, radial basis function based ANNR and LR models.

During PH estimation, R^2 = 0.719, %bias = -2.781, NSE = 0.664 and RMSE = 16.183 using SVR model whereas R^2 = 0.704, %bias = 3.456, NSE = 0.652, and RMSE =14.490 were found using ANNR model. However the values of R^2 = 0.662, %bias = 5.638, NSE = 0.627 and RMSE = 18.347 were found poor for the PH using LR model in compare to LAI, VWC, FB and DB using all three models. Figure-6 show the graphical representation between observed and estimated PH of the wheat crop by linear kernel based SVR, radial basis function based ANNR and LR models.

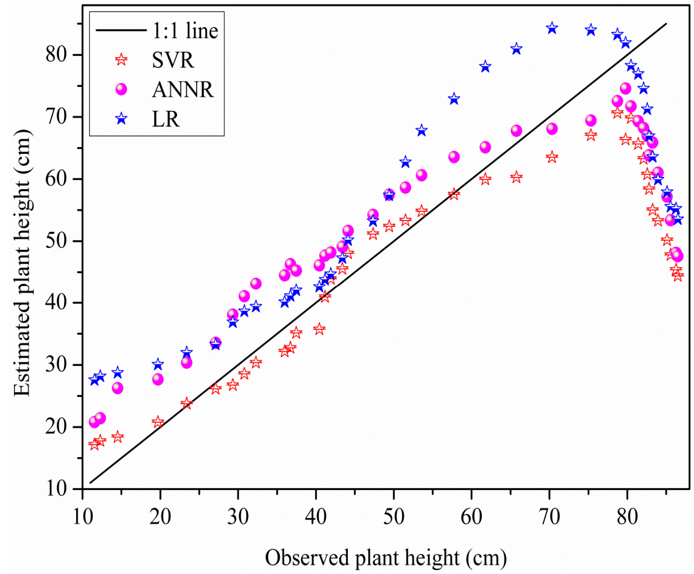

Figure-6: Graphical representation between observed and estimated plant height values of the wheat crop by linear kernel based SVR, radial basis function based ANNR and LR models.

The estimated values of PH were highly underestimated at the heading and ripening stages using SVR model. The overestimated values were found at the every stage whereas highly underestimated values were bring into being at the heading and ripening stages using radial basis function based ANNR and LR models. The estimation/retrieval of crop growth parameters by different models depends on various factors such as structure (leaf size, stem height, leaf area index, crop height, plant density etc.), crop moisture content, soil moisture, crop cover type, surface roughness, polarization, frequency, and incidence angle[43]. The under and over estimation of wheat crop growth biophysical variables at all the stages are challenging. This situation occurred in the graphs shown earlier, drawn linking observed and estimated values through more or less all models implemented in the present study.

Conclusion

The present study has shown favourable results for the estimation of VWC using C-band Sentinel-1A SAR data by linear kernel based SVR and radial basis function based ANNR models. However estimated results for LAI, DB, FB, and PH were also found good using linear kernel based SVR and radial basis function based ANNR models in compare to the LR model. The results show that the C-band, Sentinel-1A microwave satellite data may be helpful in the estimation of other type of wheat crop biophysical parameters to monitor its growth stages and its production. These outcomes may be beneficial to understand the backscattering behaviour of diverse frequencies in agricultural fields as well as may be also useful for the precise estimation of other crop growth variables and for developing new methodologies. Sentinel-1A sensor with high temporal resolution makes it very important for the larger crop monitoring user community. The enhanced radiometric resolution may reduce the estimation error of the crop growth variables. The outcomes of the current study may also be helpful for the growth stages of crop/vegetation and soil moisture retrieval by means of future satellite missions.

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