LEAF AREA INDEX ESTIMATION OF WHEAT CROP USING MODIFIED WATER CLOUD MODEL FROM THE TIME - SERIES SAR AND OPTICAL SATELLITE DATA

4.1 INTRODUCTION

The preliminary purpose of remote sensing in agricultural fields is to obtain an easy, fast, and accurate monitoring of crops for timely estimation of biophysical parameters, and other ground parameters, such as soil moisture (M_v) etc. (Taconet et al. 1994). Therefore, the use of satellite data (i.e. SAR and optical data) in agricultural fields has increased rapidly in the recent past (Beriaux et al. 2013; Champion et al. 2000). In order to retrieve reliable information about the land targets from the satellite onboard sensors, an accurate and relatively effective scattering model is needed. It is very tedious task to observe the backscattering coefficients (σ^0) of a vegetated medium in agricultural land accurately because a vegetation canopy usually comprises of various densities, shapes, sizes, and orientations of many different scatterers elements. The various scattering models for vegetation canopies have been developed using the first-order vector radiative transfer model (RTM) of vegetation after neglecting the multiple scattering from vegetation – soil layers (Feng et al. 2006; Prevot et al. 1993). LAI is one of the important growth parameters of any crop which balances the energy flux in the environment. The spatio-temporal information of LAI is often used in agriculture, ecology and climate change for global circulation models to compute energy and water fluxes (Chase et al. 1996). It is highly related to a different crops and regions of canopy processes, such as evapotranspiration, light interception, photosynthesis and respiration.

The synergy approaches of SAR with optical data were used to estimate the biophysical parameters of crops. Several physical and semi-empirical crop models have been developed for monitoring the crops and surface m_S incorporating optical and microwave satellite data (Fieuzal et al. 2011; Clevers et al. 1996; Dusseux et al. 2014). Moreover, many studies have shown that SAR data are highly dependent on biophysical parameters, such as crop height, biomass or LAI (Gao et al. 2013; Inoue et al. 2014). However, the use of optical remote sensing data (e.g., a vegetation index) is needed to calibrate the growth model for the timely estimation of LAI during the crop growth season (Clevers et al.1994). SAR data has a high temporal resolution and all-weather capability useful for timely estimation of biophysical parameters. Moreover, the optical and microwave remote sensing satellite data provide complementary information and the combined use, either time-series or at different times during the crop growth season, can improve the estimation of biophysical parameters.

The estimation of LAI using remote sensing technique would greatly improve the application of LAI as an input for mechanism of photosynthesis, crop growth models, crop type discrimination and estimation of crop yield for large areas in a cost effective way (Zheng and Moskal 2009; Xu et al. 1996). The water cloud model (WCM), proposed by Attema and Ulaby (1978) has been modified many times for the accurate estimation of crop growth parameters. Soon - Koo et al. (2015) modified the WCM by adding new parameter like leaf angle distribution of canopy to estimate the backscattering coefficients accurately. Ulaby et al. (1984) also introduced the LAI and canopy moisture using their experimental data in the model. Yang et al. (2016) estimated rice variables using improved modified WCM by incorporating different scattering layers of crop at different phenological stages with the genetic algorithm optimization technique for parameterization of the model. Liangling et al. (2016) introduced the modified WCM using vegetation fraction and integral equation model (IEM) to retrieve the LAI based on C-band RADARSAT - 2 and Landsat-8 satellite data. The modified model predicted accurate LAI with high R^2 (0.841) and low root mean square error (RMSE = 0.233 m^2/m^2) values.

The main objective of the present study is the accurate estimation of LAI using MWCM. The various studies have been carried out to modify WCM by incorporating factors like leaf area angle distribution, SAR derived vegetation descriptor and different optimization techniques for the improvement of crop biophysical parameters estimation. Some studies have incorporated the normalized difference vegetation index (NDVI) based vegetation fraction term, derived from optical data, with the SAR data for modification of WCM and found improved estimation accuracy of LAI (Clevers and Vanleeuwen 1996; Manninen et al. 2005a; Jin et al. 2015; Baghdadi et al. 2016). However, the previous study did not minimize the spatial scaling effect in the MWCM which could influence the estimation accuracy of LAI (Liangling et al. 2016). The present study demonstrates a MWCM to estimate the LAI by using C-band Sentinel-1A and Sentinel-2 satellite data. The σ^0 values were computed from Sentinel-1A SAR data whereas Sentinel-2 data were used for computation of vegetation fraction (f_{veg}) for wheat crop during its growth period. The new form of f_{veg} based on NDVI scaling correction model was used as given by Zhang et al. (2006). The field observation data along with σ^0 and f_{veg} of wheat crop at different crop growth stages and m_S variability have been used for the inversion of the MWCM for the estimation of LAI using non-linear least square optimization technique followed by lookup table (LUT) algorithm. The MWCM was found more sensitive for the estimation of LAI due to incorporation of f_{veg} in the present modified model.

4.2 MATERIALS AND METHODS

4.2.1 Study area

The study area lies at an average height of 81 m above the mean sea level in the vicinity of Varanasi district in Uttar Pradesh, India. The study area has center latitude of 25°

17′ 51″ N and longitude of 82° 56′ 36″ E covering a total area of 192 km^2. It is one of the holy cities in India located near the holy river Ganges. This area is very fertile and is in wealthy natural condition for the agriculture purpose because of its location in Indo-Gangetic plane as shown in Figure 4.1.

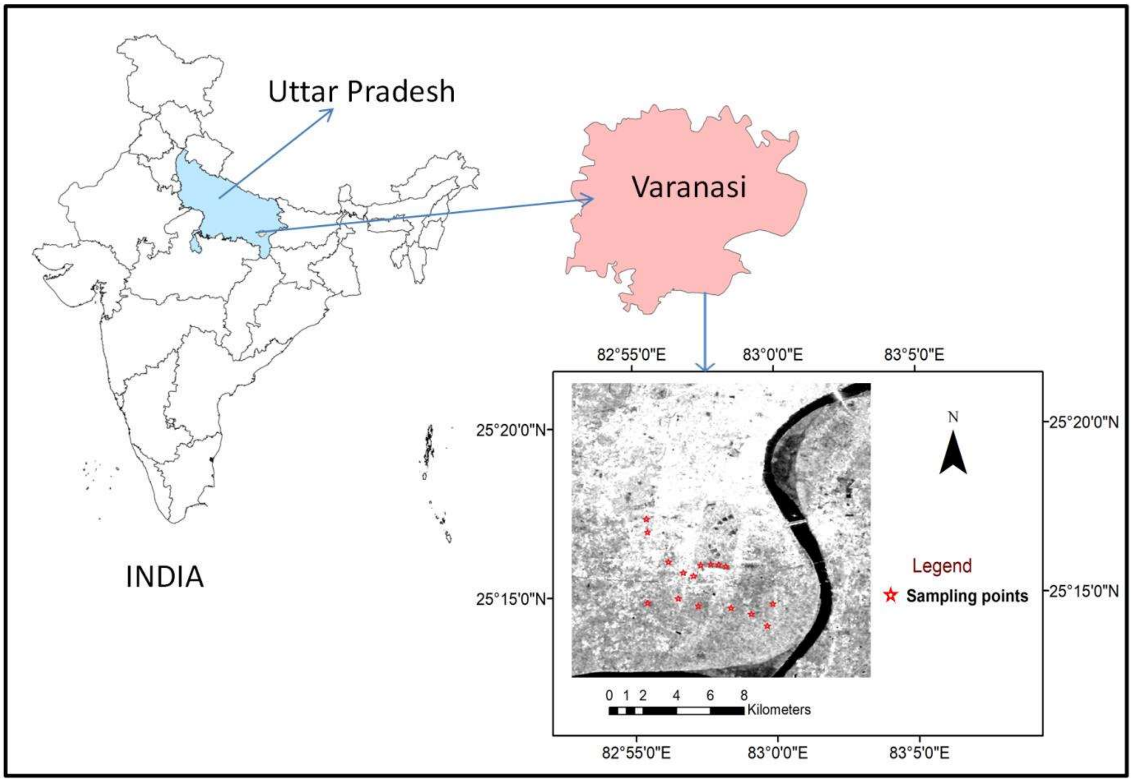

Figure 4.1. The location of study area and sampling fields

4.2.2 Field data observation

Generally, wheat is cultivated as a Rabi season crop in India. In the Rabi season, the sowing is done between October and December whereas the harvesting is generally done from March to May. In – Situ measurement of LAI and m_S were carried out between 17 January 2017 and 11 April 2017 in our investigation. The LAI measurements were made in sampling areas using an instrument namely LAI - 2200C plant canopy analyzer (LI - COR, Inc.). Whereas, the soil sampling was performed simultaneously for the dates of acquisition of satellites images and collected soil samples from the soil fields were dried in an oven at

110 °C for 18-20 hrs. These different types of samples were weighted before and after dryness for computing surface m_s which can be obtained by using relation given as,

$$M_V(\%) = \frac{W_{wet} - W_{dry}}{W_{dry}} \times 100 \qquad (4.1)$$

Where W_{wet} and W_{dry} are the weights of soil samples collected before and after dryness during field observation, respectively (Kumar, Prasad et al. 2018). The detailed information about field measurements is presented in Table 4.1.

Table 4.1. The detailed information of in-situ measurements

Sampling date	Growth stages	LAI (m^2/m^2)		m_s (%)		Sampling
		Min.	Max.	Min.	Max	points
17/01/2017	Tillering	1.4	2.2	3.2	24.8	10
10/02/2017	Jointing	2.6	3.8	4.6	28.5	13
05/03/2017	Booting	2.8	4.9	6.7	38.4	16
22/03/2017	Heading	3.1	5.8	7.8	42.2	13
11/04/2017	Ripening	2.1	4.7	5.2	34.1	12

4.2.3 Satellite data collection and Processing

In this study, both SAR and optical data have been used for the LAI estimation of wheat crop. The detail satellite data characteristics are presented in Table 4.2.

4.2.3.1 SAR Data

Sentinel-1A SAR sensor, using C-band having frequency 5.405 GHz, was launched on 3 April 2014 by the European Space Agency (ESA). The five SAR images at VV/VH - polarization of different dates between 17 January 2017 and 11 April 2017 were downloaded (https://scihub.copernicus.eu/dhus/#/home) for the full growth period of wheat crop grown in the Varanasi district. The characteristics of ground range detected (GRD) Sentinel - 1A data are described in the Table 4.2. The Sentinels Application Platform (SNAP) software version

6.0.6 toolbox (http://step.esa.int/main/download/) was used for the pre-processing of the SAR data-sets. Images were radiometrically calibrated and the speckle filtering was done using lee filter. Geometric correction was done by applying terrain correction after speckle filtering of the images. The radar cross section (σ^0) was converted from natural values to backscatter coefficient in dB units (Kumar, Yadav et al. 2018; Li et al.2018).

Table 4.2. Satellite data specifications

A) SAR (Synthetic Aperture Radar) data.						
Satellite	Date of Acquisition	Mode	Polarization	Product type	Resolution (m × m)	Level
Sentinel-1A	17/01/2017	IW	VV/VH	GRD	5 × 20	L 1
	10/02/2017	IW	VV/VH	GRD	5 × 20	L 1
	05/03/2017	IW	VV/VH	GRD	5 × 20	L 1
	22/03/2017	IW	VV/VH	GRD	5 × 20	L 1
	11/04/2017	IW	VV/VH	GRD	5 × 20	L 1
B) Optical data						
Satellite	Date of Acquisition	No. of bands	Spatial resolution (m)	Radiometric resolution	Swath (km)	Level
Sentinel-2 (MSI)	17/01/2017	13	10, 20, 60	12-bit	290	L 1
	10/02/2017	13	10, 20, 60	12-bit	290	L 1
	05/03/2017	13	10, 20, 60	12-bit	290	L 1
	22/03/2017	13	10, 20, 60	12-bit	290	L 1
	11/04/2017	13	10, 20, 60	12-bit	290	L 1

4.2.3.2 Optical Data

Sentinel-2 satellite launched on 23 June 2015, is a European Earth observation satellite. Five non cloud contaminated images of different dates (from 17 January 2017 to 11 April 2017) were downloaded from the ESA Sentinel Scientific Data Hub for the full growth period of wheat crop grown in the Varanasi district. Sentinel - 2 data carries a single payload, the Multi - Spectral Instrument (MSI) that contain 13 bands from which RED and NIR band have been used for determining the NDVI. The image pre-processing of Sentinel -2 data was done in SNAP v 6.0.6 and distributed under the GNU GPL license-3.0. The reflectance images were processed from Top – of - Atmosphere (TOA) Level 1C S2, to Bottom – of - Atmosphere (BOA) Level 2A (Muller-Wilm et al. 2016; Main-Knorn et al. 2017; Pahlevan et al. 2017b).

4.2.4. Methods

4.2.4.1. Modified Water Cloud Model (MWCM)

In WCM, the vegetation cover and vegetation layer were assumed as a homogeneous anisotropic scatterer in order to ignore the multiple scattering effects between vegetation and soil (Prasad 2011; Kumar et al. 2016; Ulaby et al. 1984). The total backscatter coefficient was mainly composed of volume scattering generated from the direct reflection of the vegetation and backscattering part produced by the ground after the double attenuation, which can be expressed as follows

$$\sigma^0(dB) = AV_1^E \cos\theta \left[1 - \exp^{\left(\frac{-2BV_1}{\cos\theta}\right)}\right] + \left(C + Dm_s\right)\exp^{\left(\frac{-2BV_1}{\cos\theta}\right)} \quad (4.2)$$

Where A, E, B, C and D are model parameters. V_1, m_s, and θ are the vegetation descriptor (i.e. LAI), m_S content and incidence angle, respectively. The Sentinel-1 measures backscattering in IW mode acquired within an incidence angle range of 29.1^0 - 46^0 (Schaufler et al. 2018). In the present study, the θ was considered 40^0 as a reference angle in MWCM.

The Equation 4.2 contains only SAR data information related to biophysical parameters. After incorporating optical data content in the form of NDVI scale invariant vegetation fraction (f_{veg}) in to Equation 4.2, the MWCM can now be expressed as:

$$\sigma^0(dB) = f_{veg} A V_1^E \cos\theta \left[1 - \exp^{\left(\frac{-2BV_1}{\cos\theta}\right)}\right] + (1 - f_{veg})\left(C + Dm_s\right)\exp^{\left(\frac{-2BV_1}{\cos\theta}\right)} \tag{4.3}$$

where

$$f_{veg} = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min} + \left(\frac{\rho_{NIR}^V + \rho_R^V}{\rho_{NIR}^S + \rho_R^S} - 1\right)(NDVI_{max} - NDVI)} \tag{4.4}$$

Where $NDVI_{min}$ and $NDVI_{max}$ are the minimum and maximum normalized difference vegetation index (NDVI) values of vegetation coverage. ρ_{NIR}^V and ρ_R^V are the surface reflectance due to vegetation coverage in NIR and RED region, respectively. While ρ_{NIR}^S and ρ_R^S are due to the soil reflectance in NIR and RED regions, respectively, which were computed using Sentinel-2 satellite image (Zhang et al. 2006).

4.2.4.2. Determination of vegetation fraction (f_{veg})

The vegetation fraction was computed using Sentinel - 2 data for wheat crop using Equation 4.4. This fraction depends on NDVI, which is one of the most important key parameter of crop to quantify the seasonal activities. NDVI values were computed using NIR and RED bands of Sentinel-2 satellite data and expressed as:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{4.5}$$

The $NDVI_{max}$ is the maximum NDVI value of wheat crop observed in the entire growth stages whereas $NDVI_{min}$ is possible minimum value of NDVI for the bare soil field.

4.2.4.3. Formulation of the objective function and inversion of model

The MWCM is function of some input parameters quantifying the crop growth variables and soil surface parameters. However, SAR signal is also directly influenced by crop growth parameters i.e. LAI, plant height (PH), vegetation water content (VWC) and bare soil properties like m_s, soil roughness and dielectric condition in vegetated areas, which is expressed in the following form

$$\sigma^0_{Mod} = f\left(LAI, m_s, f_{veg}\right) \tag{4.6}$$

The model parameters A, E, B, C and D described in Equation 4.3 were determined by running the Levenberg–Marquardt non-linear least squares optimization routine (Graham and Harris 2002) and presented in Table 4.3.

Table 4.3. Model parameters at VV and VH polarizations

Vegetation Descriptor V_1= LAI		
Model Parameter	Polarizations	
	VV	VH
A	0.061	0.103
E	1.986	2.140
B	0.284	0.257
C	-15.04	-21.13
D	24.23	23.07

The LUT algorithm was developed in MATLAB for inversion of the MWCM model for estimation of LAI after minimizing a cost function that controls the parameters over our dataset. One of the common function often used to measure the difference between the observed and the estimated value is mean squared error (MSE), which is expressed as,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\sigma^0_{i\,Obs} - \sigma^0_{i\,Mod})^2 \tag{4.7}$$

Where $\sigma^0_{i\,Obs}$ are the computed backscattering values using Sentinel-1A SAR image at VV/VH polarizations, whereas $\sigma^0_{i\,Mod}$ are the simulated backscattering values using MWCM and N is the total number of data points considered in the given study area.

4.2.5. Model performance indices

The performance of the MWCM model for the estimation of LAI was also evaluated by analyzing the different indices such as, root mean square error (RMSE) and coefficient of determination (R^2).

4.2.5.1. Root mean square error (RMSE)

The RMSE, a measure of the weighted variation in residuals between the observed and estimated values, is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{LAI_{ob}} - \mathrm{LAI_{est}})^2}{N}} \tag{4.8}$$

Where $\mathrm{LAI_{ob}}$ and $\mathrm{LAI_{est}}$ are the observed and the estimated values by MWCM, respectively and N is the total number of samples data.

4.2.5.2. Coefficient of determination (R^2)

The R^2 is statistical indicator of model performance which compares the accuracy of model between the observed and estimated values. It is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\mathrm{LAI_{ob}} - \mathrm{LAI_{est}})^2}{\sum_{i=1}^{n}(\mathrm{LAI_{ob}} - \overline{\mathrm{LAI_{ob}}})^2} \tag{4.9}$$

Where $\mathrm{LAI_{ob}}$ and $\mathrm{LAI_{est}}$ are the observed and the estimated values, respectively, while $\overline{\mathrm{LAI_{ob}}}$ is mean of the observed LAI values.

4.2.6. Validation of the methodology

The total number of observed datasets corresponding to different stages was split into model calibration and testing datasets (70 % and 30 % of the pooled data i.e. total 64 samples, respectively). Validation of the MWCM was done by using an independent dataset of wheat crop which was not used in the parameterization of the MWCM. The independent dataset consisting of LAI measurements made from the sampled fields at the time close to Sentinel -1A and Sentinel- 2 overpasses were used as a testing data-set to examine the performance and reliability of the developed model. The high R^2 and low RMSE values were obtained between observed and estimated LAI that indicated a high potential of predictive MWCM performance.

4.3. RESULTS AND DISCUSSION

4.3.1 Sensitivity of MWCM at VV/VH polarization

The MWCM showed significant potential to estimate LAI accurately and simulate the backscatter values for wheat crop at VV polarization than the VH polarization. This indicates that VV polarization is more sensitive on crop growth variables due to more dependence of its backscattering coefficients on the crop phenology like crop height, crop density, crop medium, LAI and its dielectric properties. Whereas, the cross polarization (VH) was found comparatively less sensitive because the temporal dynamic range of σ^0 for wheat crop was found more at VV polarization than that of VH polarization as shown in Figure 4.2. In order to evaluate the MWCM for the estimation of crop growth parameters, 70 % data sets were randomly chosen to determine the appropriate model parameters, and the rest was used for testing of the developed model. Figures 3 and 4 show the comparison between SAR observed and simulated backscattering coefficient computed by the MWCM and WCM at VV and VH polarizations, respectively. These Figures indicate a significant improvement for the simulation of σ^0 by the MWCM as compared to WCM. The values of R^2 were found to increase from 0.747 to 0.974 and the RMSE values were found to decrease from 0.318 to 0.208 dB using MWCM at VV polarization, whereas for VH polarization, the values of R^2 were found to increase from 0.523 to 0.732 and the RMSE values were found to decrease from 1.70 to 1.27 dB.

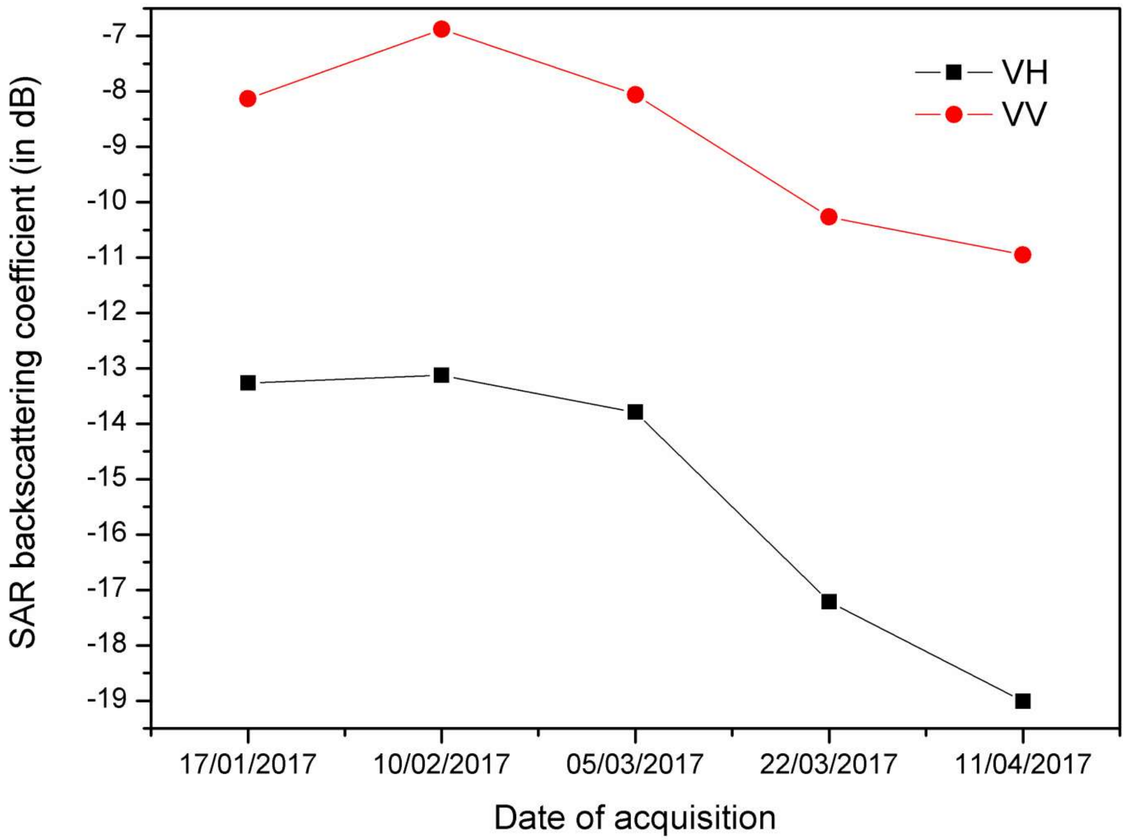

Figure 4.2. Temporal variation of backscattering coefficient of wheat crop at VV and VH polarizations

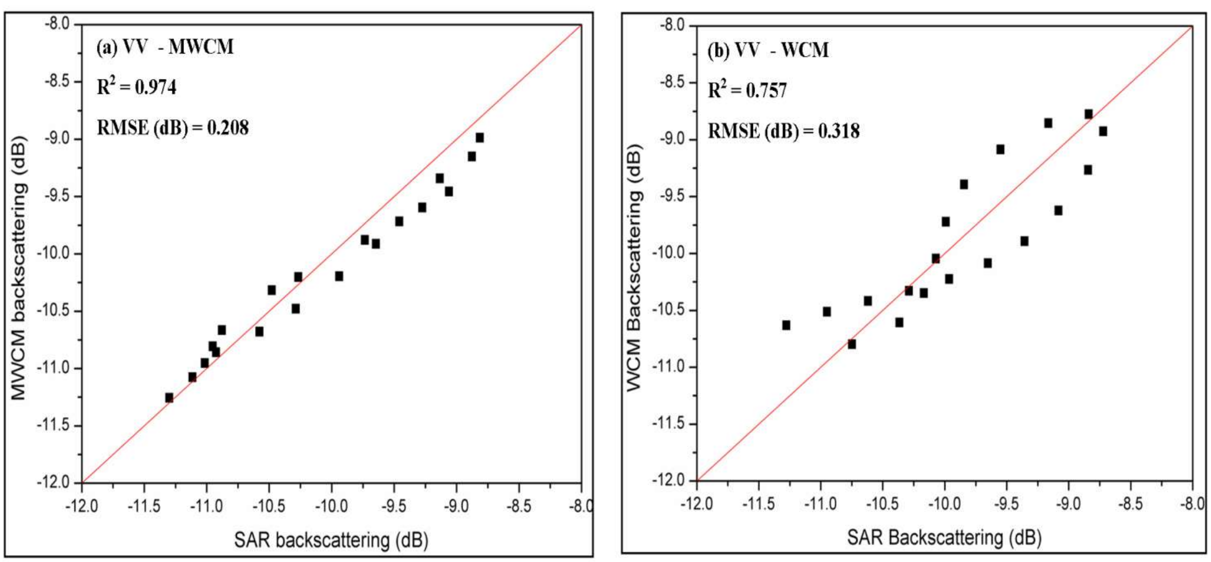

Figure 4.3. Comparison between SAR observed and simulated backscattering coefficient computed at VV polarization by (a) MWCM (b) WCM

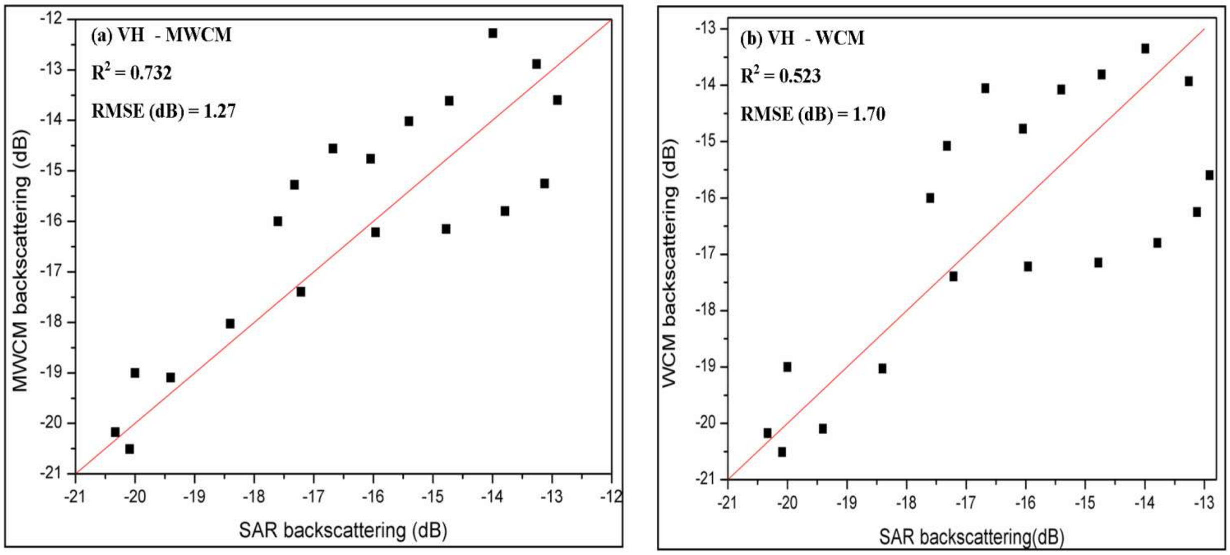

Figure 4.4. Comparison between SAR observed and simulated backscattering coefficient computed at VH polarization by (a) MWCM (b) WCM

4.3.2 Estimation of leaf area index (LAI)

LAI was estimated by the MWCM model using non–linear least square optimization technique followed by LUT algorithm. Figures 4.5 and 4.6 illustrate the graph between the observed and estimated values of LAI by the MWCM and WCM at VV and VH polarizations, respectively. The estimated values of LAI by the MWCM were found very close to the observed values as indicated by high R^2 (0.901) and low values of RMSE (0.456 m^2/m^2) than LAI values computed by WCM (R^2 = 0.696 and RMSE = 0.597 m^2/m^2) at VV polarization. At VH polarization, the LAI estimation by the MWCM also showed good correspondence (R^2 = 0.742 and RMSE = 0.521 m^2/m^2) with the observed data, whereas the estimated values of LAI by the WCM indicated poor consistency with the observed data (R^2 = 0.557 and RMSE = 0.701 m^2/m^2). Thus, the MWCM prominently showed better estimation results for LAI of wheat crop in the vegetated field than the WCM.

Temporal variation of LAI of wheat crop showed different temporal profiles due to variation in leaves density and canopy structure according to farming practices. High LAI values were observed during leaf development to flowering stage, between February and April, whereas after this time period, LAI were found to decrease significantly to low values. In the case of lower values of LAI (< 3 m^2/m^2), the radar can easily penetrate the crop canopy and get backscattered from the bare soil. However, for the dense vegetation (LAI > 3m^2/m^2), it is more complex to discriminate the vegetation and soil signal due to multiple scattering in the vegetation and soil interfaces. Therefore, it affects the estimation accuracy of crop biophysical parameters using WCM. As compared to WCM, the MWCM has a capability to decouple the vegetation background and soil background noises after adding of complementary content (f_{veg}) from Sentinel-2 satellite data at medium to high LAI values. The MWCM is related to whole growth stages of crop i.e. from tillering to ripening stages.

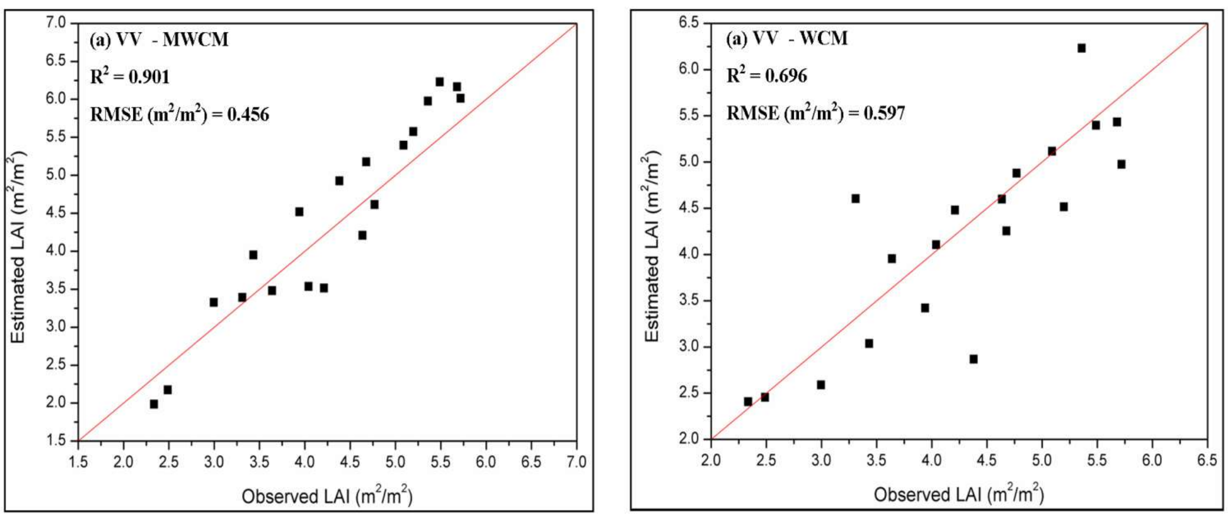

Figure 4.5. Comparison between observed and estimated LAI computed at VV polarization by (a) MWCM (b) WCM

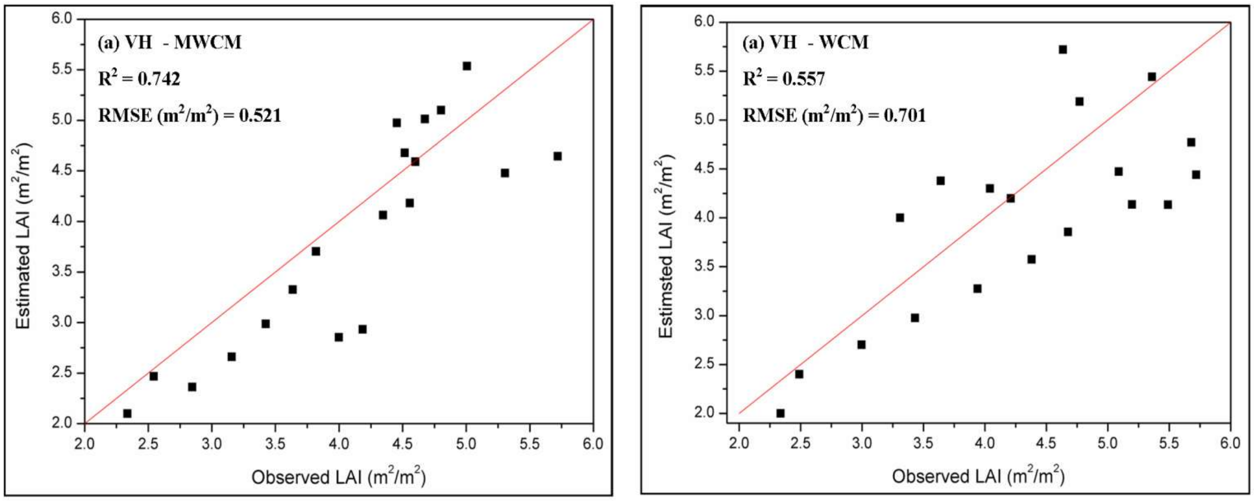

Figure 4.6. Comparison between observed and estimated LAI computed at VH polarization by (a) MWCM (b) WCM

4.3.3. The role of MWCM for improving LAI estimation

The crop canopy mainly affects the spectral reflectance in the NIR (near infrared) and visible regions. Various studies have shown that NDVI is very sensitive to low value of LAI (< 3 m^2/m^2) and comparatively less sensitive to LAI values greater than 3 m^2/m^2 (Nguy-Robertson et al. 2012). SAR data have some more advantages for the monitoring of crop phenology at low to high LAI owing to the fact that SAR sensor have higher penetration power into crop canopies and least influenced by clouds or haze. The complementary behaviour of optical and SAR data over the crop variables can support the estimation of LAI more accurate without fusion of optical and SAR satellite data (Jin et al. 2015). In WCM, the total backscattering coefficient is defined as the sum of backscatter response from vegetation and soil, only. The f_{veg} used in the present study is independent of spatial scaling effect (Zhang et al. 2006). For a mixed pixel of vegetation and soil, the f_{veg} model fairly separates the signal of vegetation and soil and minimizes the errors after the saturation level as shown in Equation 4.4. Therefore, f_{veg} scaling parameter can mitigate the saturation error in MWCM and enhance the vegetation backscattering strength in wheat crop regions through decoupling of the canopy effect and a reduction in soil signal noise influences.

4.4. CONCLUSION

The present study demonstrated high potential of MWCM for the accurate estimation of LAI by incorporating C-band Sentinel - 1A and Sentinel – 2 optical data response. This modified model introduces the full account of the backscattering response on vegetation and bare soil by adding a scale invariant vegetation fraction (f_{veg}) in the WCM. The results indicate that this MWCM has potential to provide improvements in the estimation of LAI and discrimination of the scattering response from vegetation as well as bare soil. The modelled backscattering coefficient computed by using MWCM was found better than the WCM at VV and VH polarization. Therefore, the MWCM can be applied successfully to estimate LAI of wheat crop. The estimated values of LAI by MWCM were found to show better correlation than those values of LAI obtained by WCM at VV and VH polarization. Meanwhile, the statistical analysis was found to show good correspondence (R^2 = 0.901 and RMSE = 0.456 m^2/m^2) between estimated values of LAI by MWCM and observed LAI at VV polarization. The MWCM provides a substantial way for the retrieval of biophysical parameters for crops by combining the potential of SAR and optical data. However, due to weather condition, limitation of temporal resolution of satellite data and in-situ measurement, the potential of the MWCM needs to be further verified.