ASSESSMENT OF RED-EDGE VEGETATION DESCRIPTORS IN A MODIFIED WATER CLOUD MODEL FOR FORWARD MODELING USING SENTINEL- 1A AND SENTINEL- 2 SATELLITE DATA

3.1 INTRODUCTION

The remote sensing techniques from the space platform may play important role in monitoring of vegetation condition, soil surface parameters and their relations with land-atmosphere interfaces. With high ability to penetrate vegetation canopy and top soil, the microwave synthetic aperture radar (SAR) satellite data shows great potential to extract the vegetation parameters more accurately (Mulla 2013; Paloscia et al. 2013).

In the recent past, the ample researches have been carried out to simulate the backscattered echoes from the vegetative areas using water cloud model (WCM) (Attema and Ulaby 1978). The vegetation parameters in WCM vary with the type of vegetation and its growth characteristics. Several researchers have quantified WCM vegetation parameters with different vegetation descriptors (V) (Ulaby et al. 1984; Prasad 2011). The accuracy of forward modelling from WCM depends upon the correct selection of V. So, it becomes necessary to investigate the effect of different vegetation descriptors of WCM for accurate monitoring of crop growth. Hence, the availability of fine spatio-temporal Sentinel - 2 satellite data with Red - Edge spectral band encourages the researchers to explore the Red - Edge based vegetation descriptors sensitivity in WCM for accurate retrieval of crop growth variables (Gitelson et al. 2003; Kross et al. 2015).

The adequate research has been carried out to evaluate the effect of Red - Edge vegetation indices (VI) over the vegetation canopy. They found that the Red-Edge based VI more sensitive to monitor and accurate retrieval of vegetation parameters from remotely sensed data. Therefore, the plug-in of its reflectance information over the vegetated cover fields will suppress the influences of other intermediate factors, such as leaf angle distributions and canopy complexity, which may enhance the retrieval capability of vegetation scattering model (Verrelst et al. 2015).

In this study, the modified semi - empirical vegetation scattering WCM coupled with soil geometric model was developed for simulating SAR backscattered responses in forward modelling using different vegetation descriptors (V) derived from modified Beer's law. This approach utilizes Sentinel - 1A and Sentinel - 2 satellite data to parameterize the MWCM and then simulate a large number of SAR backscattering coefficients with adoption of Red - Edge vegetation descriptors computed from modified Beer's law and some traditional V. Finally, the calibrated MWCM was applied to SAR derived observations to evaluate the robustness of developed algorithm for the simulation of backscattering coefficients (σ^0 (dB)) at VV polarization.

3.2 STUDY AREA AND DATA USED

3.2.1 Study area

In this study, the Varanasi district in India was chosen for the assessment of Red-Edge vegetation descriptors using proposed methodology. The study area lies at an average height of 81 m above the mean sea level and has center latitude 25° 17′ 51″ N and longitude 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. A moist subtropical climate with seasonal variations between winter and summer temperatures is found in Varanasi district. In this region, the soil texture changes greatly across the sampling site which results in large variation of soil moisture. It has very fertile and wealthy natural conditions for agriculture purposes because of its location in Indo-Gangetic plane, as shown in Figure 3.1.

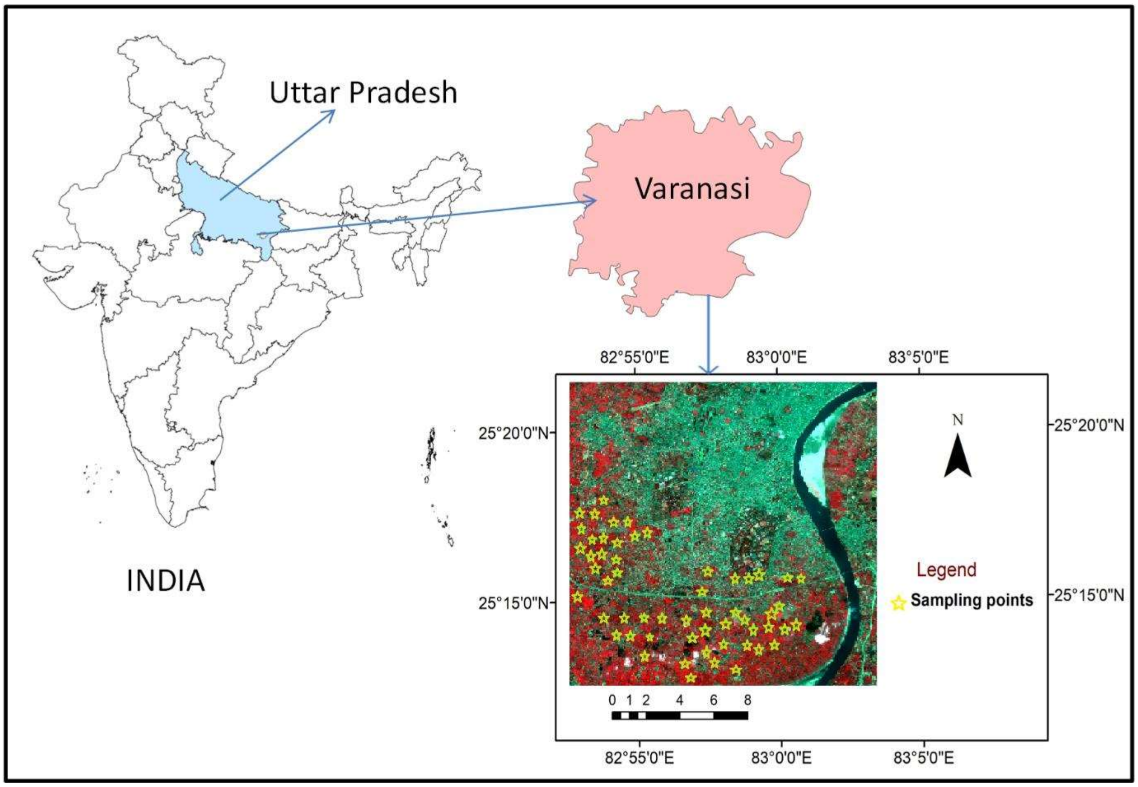


Figure 3.1 The location map of study region

3.2.2 In – situ measurements

The leaf area index (LAI) measurements were made in sampling areas using LAI - 2200C plant canopy analyzer (LI - COR, Inc.). The soil moisture contents (m_v) were taken at depth 5.0 cm in each ground locations using Hydra Probe. A one-meter long metallic plate painted with the grid of an area of 1 cm^2 was used for the measurement of roughness parameter (s). The metallic plate was pushed into the surface until the grid line reached at the lowest point on the surface. The photograph of the surface roughness profile was digitized for RMS height (h = 1.55 cm) and correlation length (l = 14.86 cm). The detailed specification of in-situ measurements is summarized in Table-3.1.

Table 3.1. The details specification of in-situ measurements for wheat crop

Sampling date	Growth stages (BBCH-Scale)	LAI (m^2 m^{-2})		m_v (%)		No. of Sampling points
		Min	Max	Min	Max	
05/02/2018	Jointing (32)	2.6	4.4	4.6	28.5	47
08/03/2018	Booting (47)	2.8	5.4	6.7	38.4	56
25/03/2018	Ripening (89)	1.7	3.8	5.2	34.1	62

3.2.3 Satellite data

In this study, the Sentinel - 1A (C - band) synthetic aperture radar (SAR) and Sentinel-2 satellite data were used to exploit the capability of modified water clod model (MWCM). Both satellite data were downloaded (https://scihub.copernicus.eu/dhus/#/home) for the different phenological stages of wheat crop grown in the Varanasi district. 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 both Sentinel - 1A and Sentinel - 2 satellite data. Moreover, the radiometric calibration and the speckle filtering (Lee filter) techniques were used for SAR images. The geometric correction was done by applying terrain correction after speckle filtering of SAR images. After that, total σ^0 was converted from natural values to backscatter coefficient in dB units (Schaufler et al.2018). Whereas, the Sentinel - 2 optical satellite data carries the Multispectral Imager (MSI) sensor and delivers 13 spectral bands (443 nm to 2190 nm electromagnetic regions) ranging from 10 to 60-meter spatial pixel size. In the Table 3.3, the RED - Band 4 (665 nm), RE - Band 7 (783 nm) and NIR-Band 8 (842 nm) reflectance values were used for computation of VI from the Sentinel-2 spectral bands. The Sentinel - 2 reflectance images were processed from Top – of - Atmosphere (TOA) Level 1C to Bottom – of - Atmosphere (BOA) Level 2A using Sen2cor processor (Main-Knorn et al. 2017). The details characteristics of both satellite data are described in the Table 3.2.

Table 3.2 The detailed specifications of satellite data

Sentinel -1A (SAR)				**Sentinel – 2 (MSI)**		
Date of Acquisition	Polarization	Product type	Resolution (m × m)	Spatial resolution	No. of bands	Radiometric resolution
05/02/2018	VV/VH	GRD	5 × 20	10, 20, 60	13	12-bit
08/03/2018	VV/VH	GRD	5 × 20	10, 20, 60	13	12-bit
25/03/2018	VV/VH	GRD	5 × 20	10, 20, 60	13	12-bit

3.3 METHODOLOGY

3.3.1 Modified water cloud model (MWCM)

In the field of microwave remote sensing for vegetation, the prominently used vegetation scattering model is the water cloud model (WCM). Here, the vegetation canopy and vegetation layer were assumed as a homogeneous anisotropic scatterer in order to ignore the multiple scattering effects between vegetation and soil (Ulaby et al. 1984). The total backscatter coefficient (σ_{T}^{0}) was mainly composed of volume scattering generated from the direct backscattering of the vegetation and the soil surface after the double attenuation, as follows

$$\sigma_{\mathrm{T}}^{0} = \sigma_{\mathrm{veg}}^{0} + \tau^{2}\sigma_{\mathrm{soil}}^{0} \tag{3.1}$$

where $\sigma_{\mathrm{veg}}^{0}$ represents the backscattered radar signal from vegetation canopy and σ_{soil}^{0} is the backscattering response from bare soil surfaces. Whereas τ^2 is defined as two-way attenuation factor through vegetation-soil interfaces.

$$\sigma_{\mathrm{veg}}^{0} = f_{\mathrm{veg}} A V^{E} cos\theta \left[1 - \exp\left(\frac{-2 \times B \times V}{cos\theta}\right)\right] \quad (3.2)$$

$$\tau^2 = \exp\left(\frac{-2 \times B \times V}{cos\theta}\right) \quad (3.3)$$

$$\sigma_{\mathrm{T}}^{0} = f_{\mathrm{veg}} A V^{E} cos\theta \left[1 - \exp\left(\frac{-2 \times B \times V}{cos\theta}\right)\right] + \exp\left(\frac{-2 \times B \times V}{cos\theta}\right)\left\{(1 - f_{veg})\sigma_{soil}^{0}\right\} \quad (3.4)$$

The $\sigma_{\mathrm{soil}}^{0}$ at VV polarization can be expressed in term of soil Fresnel reflectivity (Γ). It also represents the rough surfaces scattering term approximated by geometrical model (Kseneman et al. 2011). This can be defined as:

$$\sigma_{\mathrm{soil}}^{0}(\mathrm{VV}) = \frac{|\Gamma|^2 \exp(\frac{-\tan^2\theta}{2\,s^2})}{2s^2\cos^4\theta} \quad (3.5)$$

In the above expression, the surface roughness parameter ($\mathrm{s} = \frac{\sqrt{2\mathrm{h}}}{\mathrm{l}} = 0.118$) may be defined in terms of RMS height (h), correlation length (l) and incidence angle ($\theta = 40^{\circ}$). Whereas, the soil Fresnel reflectivity (Γ) is given in Equation (3.6)

$$\Gamma = \left|\frac{\varepsilon_s\cos\theta - \sqrt{\varepsilon_s - \sin^2\theta}}{\varepsilon_s\cos\theta + \sqrt{\varepsilon_s - \sin^2\theta}}\right| \quad (3.6)$$

In the soil Fresnel reflectivity, the ε_s is the relative soil dielectric constant (Du et al. 2000), which can be computed by using Equation (3.7)

$$\varepsilon_s = 114\, m_{\mathrm{v}}^2 + 13.3\, m_{\mathrm{v}} + 2.5 \quad (3.7)$$

In the vegetative areas, the satellite spectral pixels are linear mixture with crops and bare soil responses with some area weightage f_{veg} for crops and (1 - f_{veg}) for the bare soil. Therefore, the vegetation fraction (f_{veg}) in Equation (3.4) can be defined as:

$$f_{\text{veg}} = \frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}} + \left(\frac{\rho_{\text{NIR}}^{\text{V}} + \rho_{\text{R}}^{\text{V}}}{\rho_{\text{NIR}}^{\text{S}} + \rho_{\text{R}}^{\text{S}}} - 1\right)(\text{NDVI}_{\text{max}} - \text{NDVI})} \tag{3.8}$$

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

3.3.2 Red-Edge vegetation descriptor

The Red-Edge based vegetation indices (VI) were computed from Sentinel -2 satellite data. The modified Beer's law (Jin and Eklundh 2014) was used to derive the final vegetation descriptors (V) using Equation (3.9).

$$V = VI_{\infty} - (VI_{\infty} - VI_0) \times \text{e}^{(-K_{\text{VI}} \times \text{LAI})} \tag{3.9}$$

where VI_{∞} and VI_0 are the VI values for dense vegetation and bare soil, respectively. Whereas K_{VI} is the vegetation extinction coefficient which may theoretically be affected by leaf angle distribution, sensor viewing geometry and types of canopy structure (Broge and Mortensen 2002). The detailed specifications of vegetation descriptors (V) in MWCM are shown in Table 3.3

Table 3.3 The selected Red-Edge VI and others known vegetation descriptors (V) in MWCM

A) Red-Edge (RE) based vegetation descriptor in WCM			
Vegetation descriptor	(VI)	Name	Formula
$\boldsymbol{V} = \boldsymbol{VI}_{\infty} - (\boldsymbol{VI}_{\infty} - \boldsymbol{VI}_{\mathbf{0}}) \times \mathbf{e}^{(-K_{\mathrm{VI}} \times LAI)}$	$\mathrm{NDVI_{RE}}$	Red-Edge normalized difference vegetation index	$\frac{(NIR - RE)}{(NIR + RE)}$
	$\mathrm{MSR_{RE}}$	Modified simple ratio Red-Edge	$\frac{(NIR/RE - 1)}{(\sqrt{NIR/RE + 1})}$
	$\mathrm{CI_{RE}}$	Chlorophyll index Red-Edge	$\frac{NIR}{RE} - 1$

B) Others well known vegetation descriptors in WCM		
(V)	Name	Formula
NDVI	Normalized difference vegetation index	$\frac{(NIR - RED)}{(NIR + RED)}$
LAI	Leaf area index	One-sided green leaf area per unit ground surface area (m^2m^{-2})

3.3.3 Model performance indices in the forward modeling

The developed model evaluation was assessed by the following indices:

(1) The coefficient of determination (**R^2**) is primary computational statistical indicator for model evaluation which measures the agreement between the observed and simulated values by the developed model. It is expressed as:

$$R^2 = \left(\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} \left(\sigma_{SAR}^0 - \overline{\sigma_{SAR}^0}\right)\left(\sigma_{mod}^0 - \overline{\sigma_{mod}^0}\right)}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}} \left(\sigma_{SAR}^0 - \overline{\sigma_{SAR}^0}\right)^2} \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}} \left(\sigma_{mod}^0 - \overline{\sigma_{mod}^0}\right)^2}} \right)^2 \quad (3.10)$$

(2) The root mean square error (RMSE) computed the variation in residuals between the observed and simulated values, is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\sigma_{SAR}^{0} - \sigma_{mod}^{0})^2}{N}} \quad (3.11)$$

(3) The Nash Sutcliffe efficiency (NSE) measures the robustness of the developed model and expressed as:

$$NSE = 1.0 - \frac{\sum_{i=1}^{N}\left(\sigma_{SAR}^{0} - \sigma_{mod}^{0}\right)^2}{\sum_{i=1}^{N}\left(\sigma_{SAR}^{0} - \overline{\sigma_{SAR}^{0}}\right)^2} \quad (3.12)$$

Where σ_{SAR}^{0} and σ_{mod}^{0} are the SAR computed and the modelled backscattering coefficient values, respectively. The $\overline{\sigma_{SAR}^{0}}$ and $\overline{\sigma_{mod}^{0}}$ are the average value of the SAR computed and the modelled backscattering coefficient values, respectively. Whereas, the N define as total number of data set.

3.4. RESULTS AND DISCUSSION

3.4.1. Determination of VI_0, VI_∞ and K_{VI} for different vegetation descriptors

The value of VI_0 for bare soil of each selected VI of Red-Edge indices were computed from the Sentinel -2 data taken on March 27, 2018. Whereas, the value of both VI_∞ and K_{VI} in the modified Beer's law (Equation (3.9)) were estimated using non-linear least square optimization algorithms for each of selected indices over the wheat crop fields. The optimum values of estimated parameters are shown in the Table 3.4.

Table 3.4 The optimized model parameters of modified Beer's law

Vegetation Index	VI_0	VI_∞	K_{VI}
$NDVI_{RE}$	0.127	0.612	0.602
MSR_{RE}	0.201	1.081	0.456
CR_{RE}	0.321	2.417	0.342

3.4.2 Computation of model parameters in MWCM

The model parameters in Equation 3.4 are mainly correlated to types of vegetation and canopy structure. Therefore, the training data sets (two-third of pooled data) were chosen for the parameterization of MWCM for selected vegetation descriptors at VV polarization. The non-linear least square optimization algorithms were adopted for the computation of A, E and B model parameters. The optimum value of MWCM parameters for different vegetation descriptors are shown in Table 3.5.

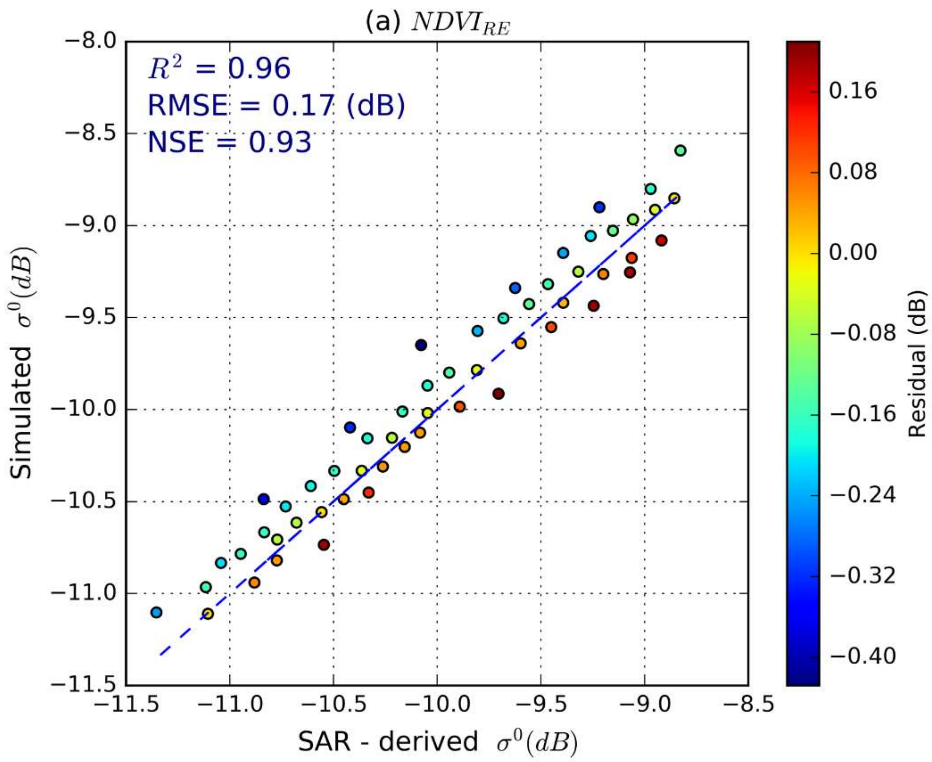
Table 3.5 The values of model parameters of different vegetation descriptors (V) used in MWCM

Model parameters	$NDVI_{RE}$	MSR_{RE}	CR_{RE}	NDVI	LAI
A	0.296	0.457	0.701	0.178	0.096
E	1.97	2.02	1.21	2.37	1.42
B	0.293	0.388	0.576	0.263	0.288

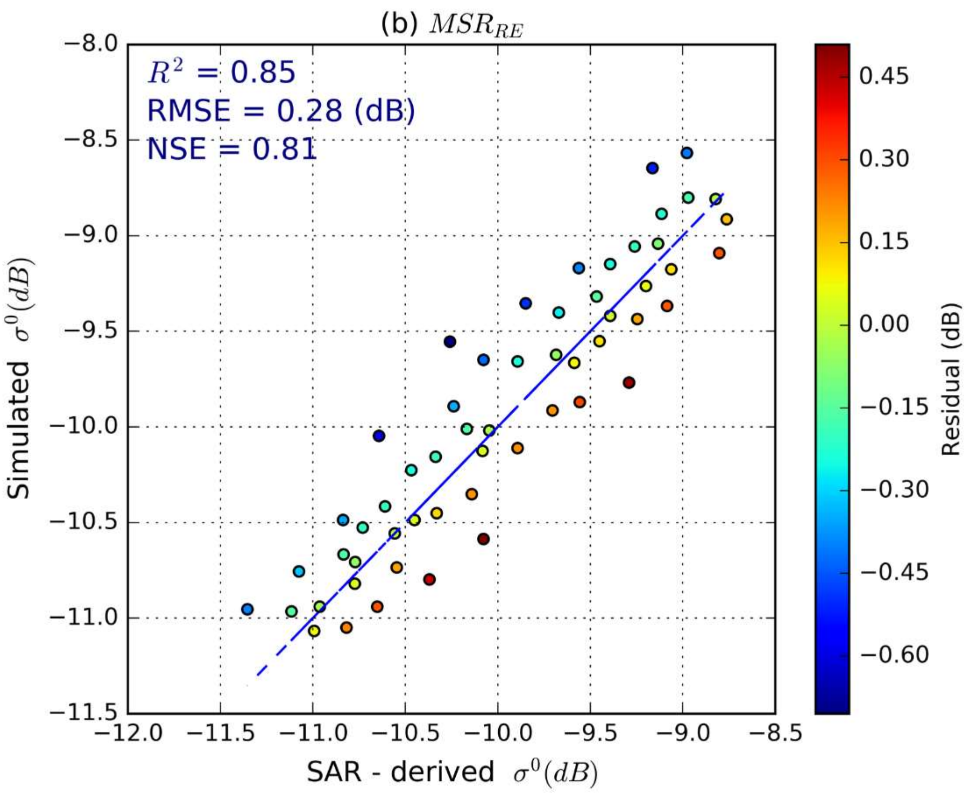
3.4.3 Simulation of backscattering coefficient (σ^0 (dB)) in forward modelling using MWCM

The present study assessed the potential of red-edge based vegetation descriptors in developed MWCM over the wheat crop. After the calibration of proposed algorithm, the selected V derived from the modified Beer's law were tested in MWCM for the simulation of backscattering coefficients (σ^0 (dB)) at VV polarization. The interfering physical factors used in MWCM were Γ, ε_s and f_{veg} which may directly be affected by crop and soil variables. The inclusion of these surface parameters in MWCM led to build robust vegetation scattering algorithm.

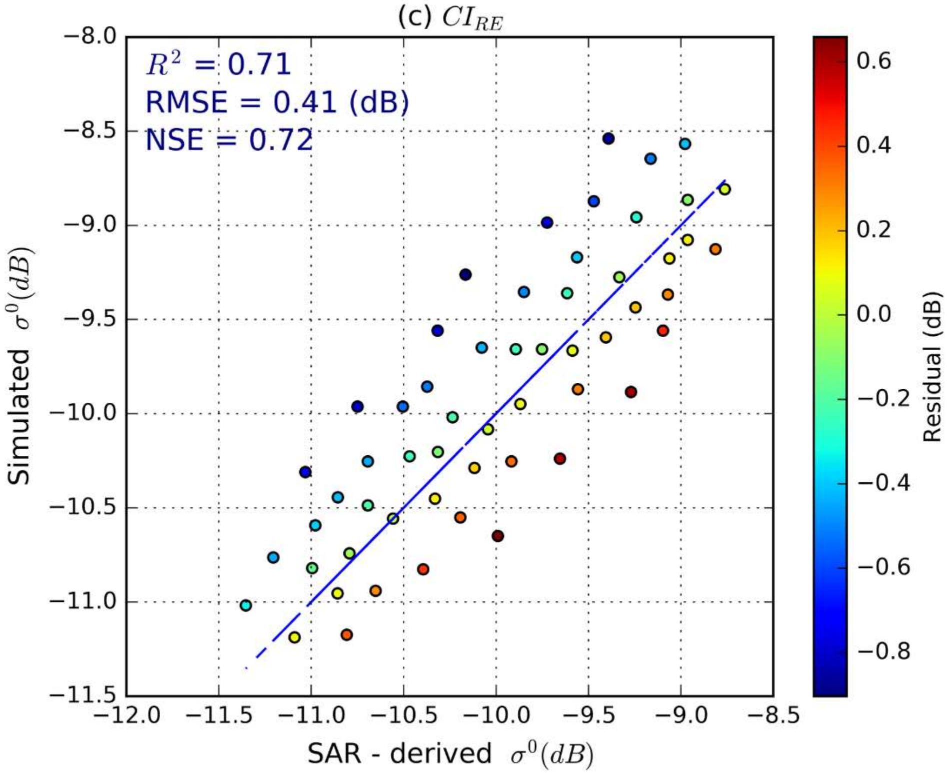
Figure 3.2 showed that the comparison of simulated σ^0 (dB) using MWCM and SAR-derived σ^0 (dB).The Figure 3.2(a) showed higher correlation between simulated and SAR derived σ^0 (dB) for vegetation descriptors (V) derived by modified Beer's law using VI = $NDVI_{RE}$. Among all vegetation descriptors, the highest performance results (R^2 = 0.96, RMSE = 0.17 (dB) and NSE = 0.93) were found for VI = $NDVI_{RE}$ computed using Equation 3.9. Whereas, the others vegetation descriptors like MSR_{RE}, CI_{RE}, NDVI and LAI showed relatively lower performance for simulating σ^0 (dB) in the forward modelling. The vegetation fraction (f_{veg}) can play as a tool to characterize the correct amount of backscattering responses from each vegetation and soil surface. Therefore, the performance indices showed that the dependency of soil geometrical model (roughness parameters) used in the MWCM yielded great capability to build the completeness of backscattered responses owing the facts of Red-Edge VI reflectance over the wheat covered fields. However, MWCM is not only suitable for the surface with vegetation coverage, but also for the surface with uneven or sparse vegetation coverage. This is important for simulating the σ^0 (dB) during wheat crop growth stages. The key factor of the Red-Edge based VI is that they are less influenced by canopy structures and are more promising for building a generic model for different crops than the visible indices (Nguy-Robertson and Gitelson, 2015). Alternatively, in vegetative areas, the satellite sensed spectral pixels are mixed with crops and bare soil with some area fraction f_{veg} for crops and (1 - f_{veg}) for the bare soil.



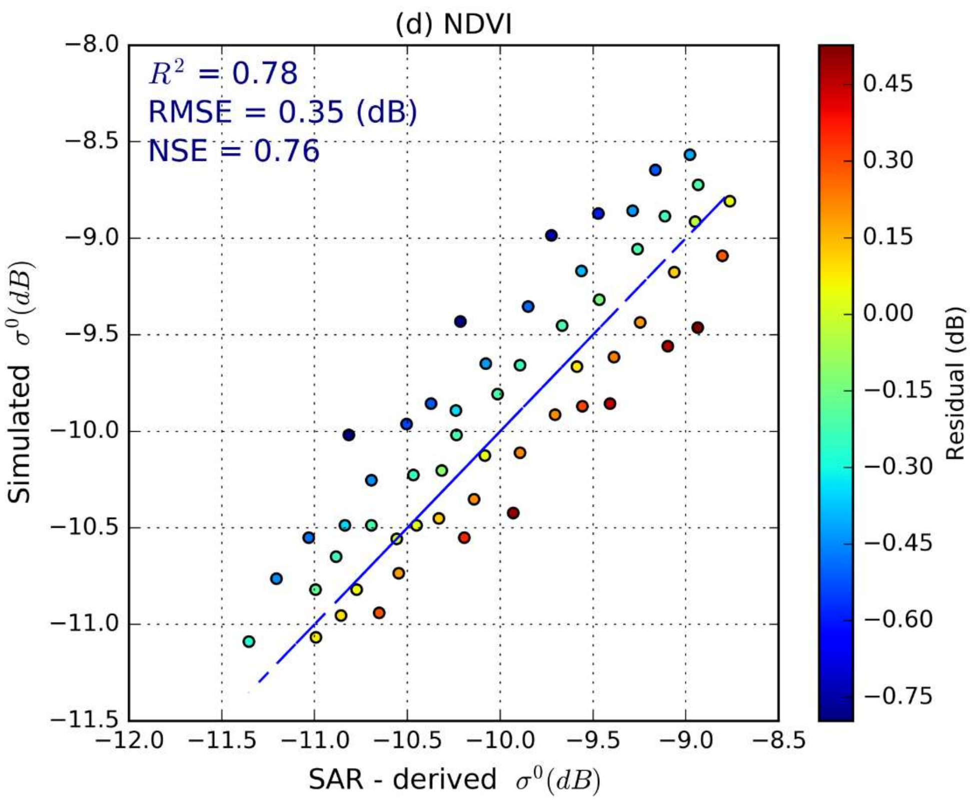
(a) $NDVI_{RE}$
R^2 = 0.96
RMSE = 0.17 (dB)
NSE = 0.93
Simulated $\sigma^0(dB)$
SAR - derived $\sigma^0(dB)$
Residual (dB)



(b) MSR_{RE}
R^2 = 0.85
RMSE = 0.28 (dB)
NSE = 0.81
Simulated $\sigma^0(dB)$
SAR - derived $\sigma^0(dB)$
Residual (dB)



(c) CI_{RE}
R^2 = 0.71
RMSE = 0.41 (dB)
NSE = 0.72
Simulated $\sigma^0(dB)$
SAR - derived $\sigma^0(dB)$
Residual (dB)
−8.0
−8.5
−9.0
−9.5
−10.0
−10.5
−11.0
−11.5
−12.0
−11.5
−11.0
−10.5
−10.0
−9.5
−9.0
−8.5
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8



(d) NDVI
R^2 = 0.78
RMSE = 0.35 (dB)
NSE = 0.76
Simulated $\sigma^0(dB)$
SAR - derived $\sigma^0(dB)$
Residual (dB)
−8.0
−8.5
−9.0
−9.5
−10.0
−10.5
−11.0
−11.5
−12.0
−11.5
−11.0
−10.5
−10.0
−9.5
−9.0
−8.5
0.45
0.30
0.15
0.00
−0.15
−0.30
−0.45
−0.60
−0.75

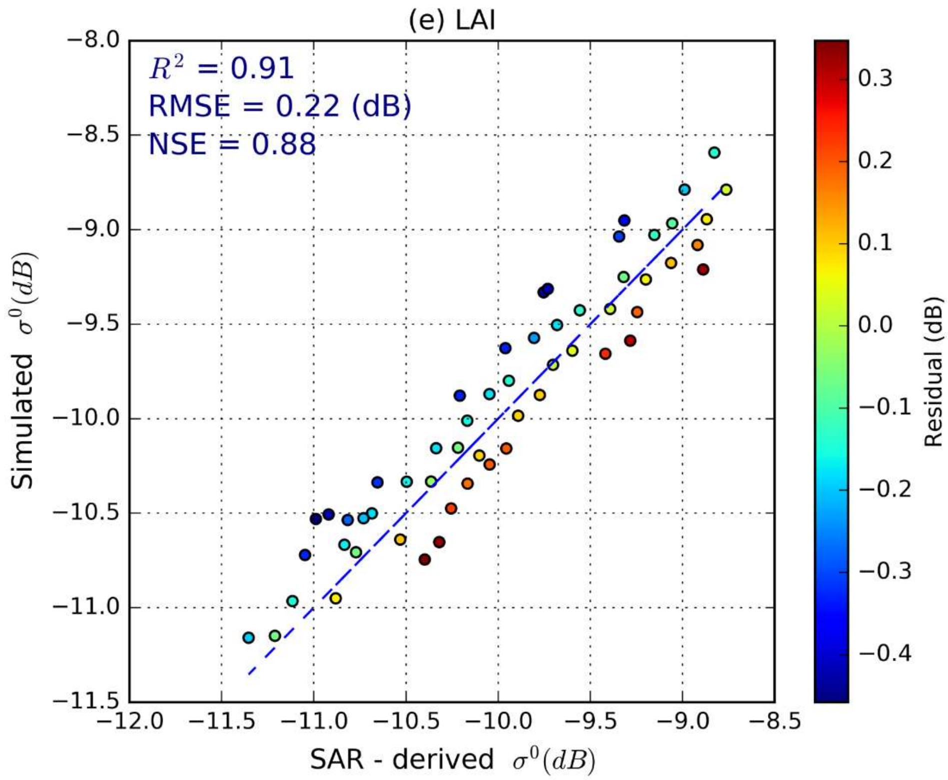


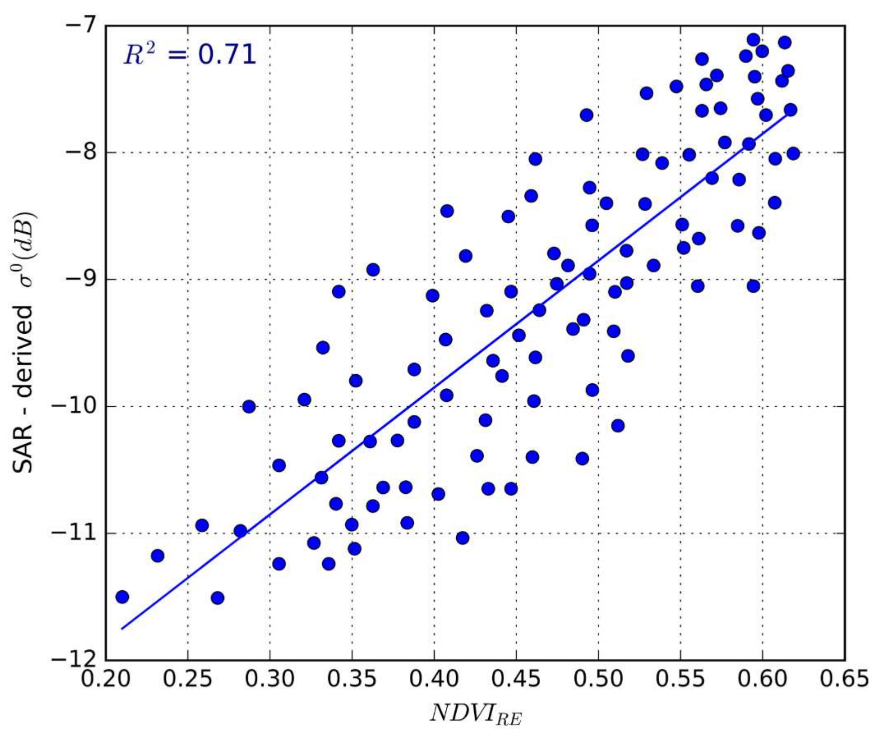
Figure 3.2 Assessment of forward modeling simulation computed by using the vegetation descriptors ($NDVI_{RE}$, MSR_{RE}, CI_{RE}, NDVI and LAI) in MWCM at VV polarization

3.4.4 Sensitivity of $NDVI_{RE}$, MSR_{RE}, and CI_{RE} in MWCM

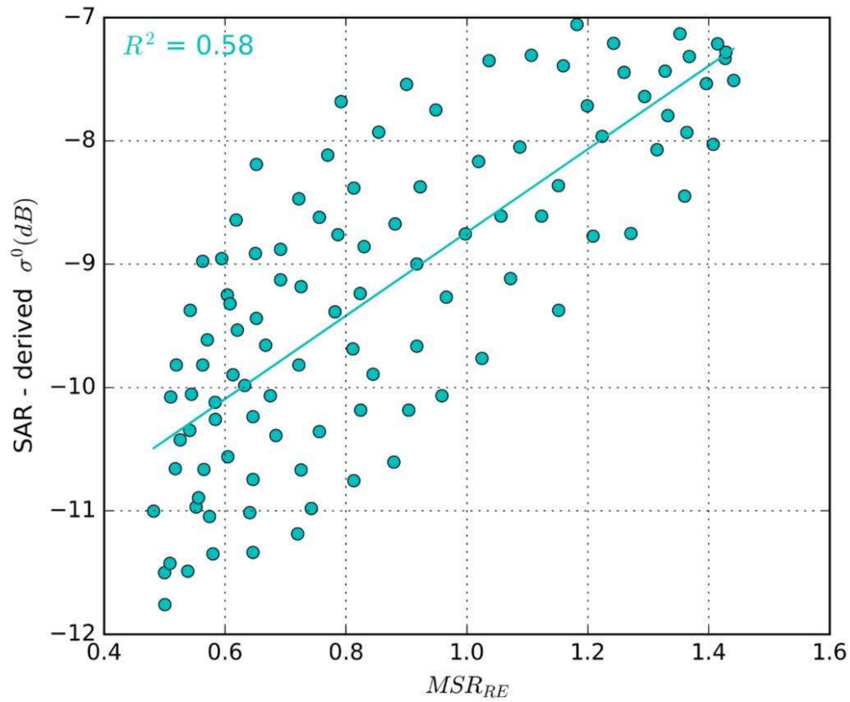
The simulation of backscattering echoes, in forward direction from the vegetation and soil surfaces using water cloud model, is highly sensitive to their selection of vegetation descriptor parameters, optimized model parameters and inversion algorithms.

The Red-Edge ($NDVI_{RE}$) indices are better indicator of vegetation vigor phenology than NDVI for mid to late season crops (LAI > 3 m^2 m^{-2}) that have accumulated high levels of chlorophyll in their leaves because Red-Edge light is more transparent to leaves than red light and so it is less likely to be completely absorbed by a canopy (Dong et al. 2019). Therefore, it is more efficient than NDVI for intensive applications throughout the growing season because NDVI often loses sensitivity after getting accumulation of a critical level of leaf cover (saturation level) or chlorophyll in the plant. However, the MSR_{RE}, and CI_{RE} are comparatively less sensitive than $NDVI_{RE}$ during different crop growth, leaves architecture and leave angle distribution due to more absorption and scattering effect (Xiao et al. 2014). Figure 3.3 showed the comparative analysis of $NDVI_{RE}$, MSR_{RE}, and CI_{RE} with Sentinel - 1A derived backscattering coefficient (σ^0(dB)). The $NDVI_{RE}$ indicated reasonably high correlation (R^2 = 0.71) with σ^0(dB) than MSR_{RE}, and CI_{RE}. The VIs calculated from Sentinel - 2 data directly inserted in MWCM showed ~~s~~ saturation effect and inherently created more contamination signal during the forward simulation. Therefore, the Equation 3.9 was used in the study to reduce the complexity of saturation level and enhanced the more accurate simulation from the MWCM. Therefore, the selection of $NDVI_{RE}$ based vegetation descriptor derived from modified Beer's law would be highly sensitive in MWCM for the simulation of backscattered echoes in the forward direction.

(a)



(b)



(c)

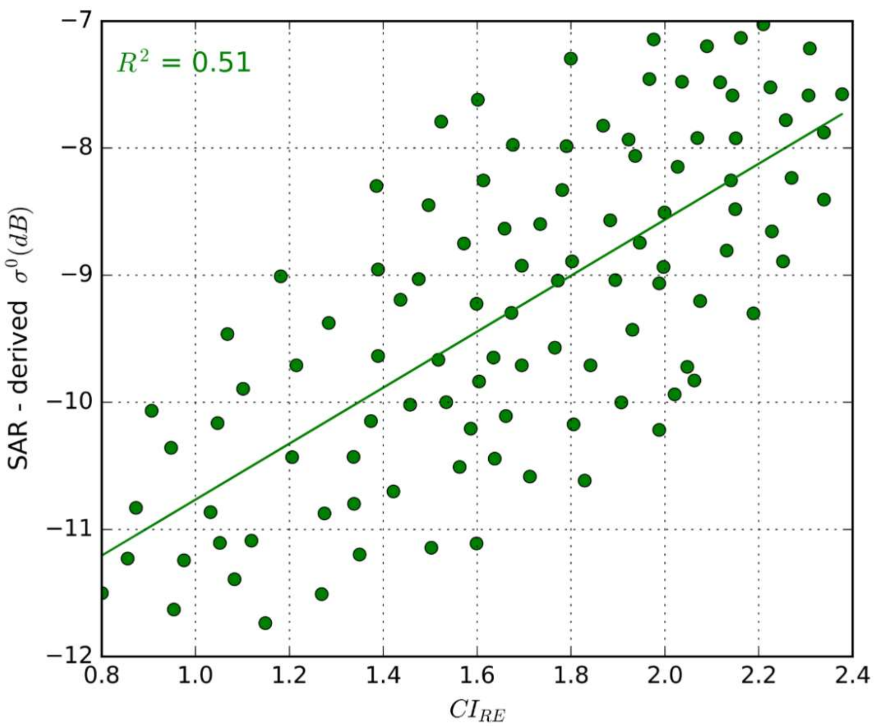


Figure 3.3 Comparative analysis of (a) $NDVI_{RE}$, (b) MSR_{RE}, and (c) CI_{RE} with Sentinel - 1A SAR derived σ^0(dB) at VV polarization

3.5. CONCLUSION

In this study, the Red-Edge based vegetation descriptors were selected to assess its potential for forward modelling applied in MWCM using Sentinel - 1A (C - band) and Sentinel - 2 satellite data. The results of the present study confirmed the high potential of the developed semi-empirical MWCM for the simulation of σ^0 (dB) in the forward modelling. Therefore, the present study explored the following majors scientific out-comes:

(1) The MWCM algorithm using Sentinel - 1A (central frequency 5.405 GHz) could be more robust for the simulating the backscattered signal in the vegetated and non-vegetated covered fields due to capability of day-night data acquisition, higher penetration depth and independent of almost all weather conditions.

(2) This study reveals that the $NDVI_{RE}$ Red - Edge based vegetation descriptor computed from modified Beer's law could be more robust vegetation parameter used in MWCM for forward and inverse modelling.

(3) The MWCM, coupled with equivalent roughness using geometrical model of soil surfaces, does not require other measured surface roughness parameters.

Therefore, the developed MWCM may be the powerful vegetation scattering model for the accurate mapping and retrieval of biophysical parameters using time-series Sentinel - 1A SAR data, which may become more time continuous with the constellation of Sentinel - 1A and Sentinel - 1B satellites in near future.