Evaluation of Radar Backscattering Models IEM, OH, and Dubois using L and C-Bands SAR Data over different vegetation canopy covers and soil depths

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ABSTRACT:

Several algorithms have been proposed in the literature to invert radar measurements to estimate surface soil moisture. The objective of this paper is to compare the performance of the most common surface back scattering models including the theoretical integral equation model (IEM) of Fung et al(1992)., and the semi-empirical models of Oh et al (1992, 1994, 2002 and2004). and Dubois et al (1995).. This analysis uses four AIRSAR data in L and C band together with in situ measurements (soil moisture and surface roughness) over bare soil and vegetation covers area and three different soil depths. The results show that Dubois model tend to over-estimate the radar response in both bands while IEM model and Oh model frequently over-estimate the radar response in L band but under-estimate them in C band. By evaluating of all models in different soil depths, the best results were obtained in 0-3 cm depths. For vegetation area poor correlation between models backscatter simulation and radar response was observed.

1. Introduction

Soil moisture is an important parameter in many applications such as hydrology, agriculture, risk prediction and climate studies (Alvarez-Mozos et al., 2005; Beljaars et al., 1996; Georgakakos et al., 1996). Due to the high dependence of the microwave dielectric constant on soil water content, there is a high correlation between the radar backscattering coefficient and soil moisture (Panciera et al., 2009; Srivastava et al., 2009). Accordingly, much research has been done in the past to estimate soil moisture using Synthetic Aperture Radar (SAR) images (Ulaby et al., 1996; Zribi et al., 2008;; Song et al., 2009) and different empirical, semi-empirical, and theoretical soil moisture estimation models have been developed (Atemma and Ulaby, 1978; Oh et al., 1992; Fung et al.,). Among the numerous semi-empirical models reported in the literature the most popular ones are those developed by Oh (Oh et al. 1992, 1994, 2002, Oh 2004) and Dubois et al. (1995). The Oh model uses the ratios of the measured backscatter coefficients $p = \sigma^0_{HH} / \sigma^0_{VV}$ and $p = \sigma^0_{HV} / \sigma^0_{VV}$, and cross-polarized backscatter coefficient σ^0_{HV} to estimate volumetric soil moisture and surface roughness, while the Dubois model links the backscatter coefficients in HH and VV polarizations to the soil's dielectric constant and surface roughness. The physical approach uses theoretical models that predict the radar backscatter coefficient from radar parameters and soil characteristics. The physical models provide site-independent relationships, but have limited roughness domains. The integral equation model (IEM) (Fung et al. 1992) is the most commonly used physical model in inversion procedures for the retrieval of soil moisture and/or roughness parameters.
Extensive studies have evaluated various models, but conflicting results have been obtained. Some studies have shown good agreement between measured backscatter coefficients (Rakotoarivony et al. 1996, Zribi et al. 1997, Satalino et al. 2002) and those predicted by the models, while others have found great discrepancies between them (Shi et al. 1997, Bindlish and Barros 2000, Baghdadi et al. 2004). The objective of this research is to evaluate and compare the accuracies of the three most popular models used in inversion procedures (the Oh, Dubois and IEM models) using L and C bands over different soil depths and vegetation canopy cover.

2. Database

2.1. Study area

The study area is located in southwest Oklahoma in the Southern Great Plains region of the United States and covers an area of 611 sq. km. The Little Washita Experimental Watershed (LWREW) is the focus of the Southern part of Oklahoma (OS) which is dominated by grassland. The location of these regions is shown in Figure 1, which is a Landsat-5 TM images collected on 10 July 2003. Figure 1 shows a combination of bands 4, 3, and 2 as the red, green, and blue channels. Red, white, and blue pixels indicate vegetation, bare soil, and dormant or senescent vegetation, respectively. The specifications of the study area are shown in Table 1.

2.2. Field data

The data used in this study is the Soil Moisture Experiments (SMEX03) data set that was gathered on 10 June 2003.

Study Site	Location		Vegetation	topography	Range of mv (%)	Range of rms (cm)
Little Washita Watershed	Corner NW	35.01 N 98.03 W	rangeland and pasture (63%) with significant areas of winter wheat	moderately rolling	0.7 – 28.8	0.6592- 2.0927
	Corner SE	34.75 N 97.89 W				

Table 1. Study area

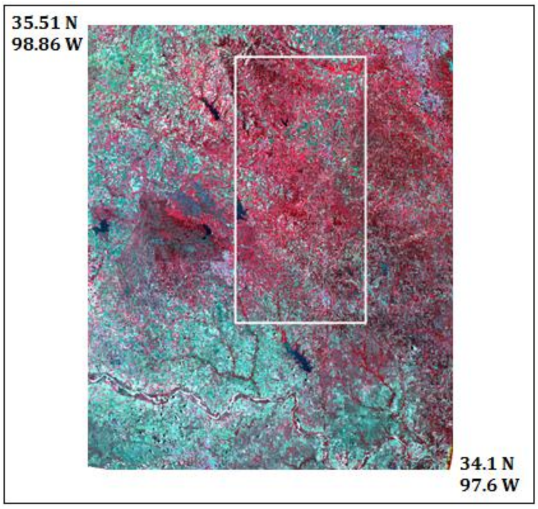

Figure 1. Landsat-5 TM image showing the general locations of the study region.

Sampling was performed on sites approximately one-quarter section, 0.8 km by 0.8 km, in size. Soil samples were collected and soil temperature, surface temperature, soil dielectric constants were measured. In each site, soil moisture at 0-6 cm soil depth was measured using theta probe (TP). Also, at the time of sampling, a sampling tool was used to extract VSM and bulk density (BD) of 0-3 cm and 3-6cm soil depth layers. The little Washita watershed dataset contains 13 sites and 54 points in all these sites. From total 54 sample points, 16 points have NDVI values in the range of 0-0.2 and 16 points have NDVI values in the range of 0.2-0.4 and 20 points have NDVI values in the range of 0.4-0.6. A 1 m roughness tablet was used to measure surface roughness. First the grid board was placed on soil vertically and a photo was taken. Then using these photos surface heights were digitized

at about 0.5 cm intervals, and then the root mean squared height (h_{rms}) parameter was calculated: (http://nsidc.org/data/docs/daac/nsidc0345_smex03_ancillary_surface_roughness/index.html)

$$h_{rms}=\left(\frac{1}{n}\sum_{i=1}^{n}(Z_i-\bar{Z})^2\right)^{1/2} \tag{1}$$

Where n is the number of measurements of the height, Z_i is a single measurement, and $\bar{Z}$ is the mean of the measurements. To determine the correlation length and the correlation length function, the surface autocorrelation curve was computed. Once the autocorrelation curve has been computed, the correlation length can be determined. The correlation length is defined as the distance *(d)* at which the autocorrelation is less than e^{-1}. The correlation length can then be used to fit the theoretical correlation function to the measured autocorrelation curve by optimizing the power coefficient *(n)*.

2.3. Satellite data

In this study four Airborne Synthetic Aperture Radar (AIRSAR) images were used. AIRSAR is side-looking airborne radar and its data is in Stokes matrix format with a pixel size of 6.66 m in range and 9.26 m in azimuth. The incidence angle varies between 20° and 70°. The images were taken in polarimetric mode (POLSAR) and are used to produce SMEX03. In this mode data is collected in three frequencies C, L, and P and in four different polarizations HH, VV, HV, and TP (total power). The data used in this research were acquired in frequency L and C and polarization HH, HV, and VV. One Landsat-5 TM images were also used in this research. SAR and optical images were acquired 10 June 2003.

3. Description of scattering models

3.1. The Integral equation model

The IEM is a theoretical backscattering model applicable to a wide range of roughness values (Fung et al. 1992). The backscatter coefficient of the surface contribution is expressed as:

$$\sigma^0_{pq}=\frac{k^2}{2}\exp(-2k_z^2\sigma^2)\sum_{n=1}^{\infty}\sigma^{2n}\left|I^n_{pq}\right|^2\frac{W^n(-2k_x,0)}{n!} \tag{2}$$

With

$$I^n_{pq}=(2k_z)^n f_{pq}\exp(-k_z^2\sigma^2)+\frac{k_z^n[F_{pq}(-k_x,0)+F_{pq}(k_x,0)]}{2} \tag{3}$$

$$f_{VV}=\frac{2R_{\parallel}}{\cos\theta} \tag{4}$$

$$f_{HH}=\frac{2R_{\perp}}{\cos\theta} \tag{5}$$

$$W^n(k_x,k_y)=\frac{1}{2\pi}\iint\rho^n(x,y)\exp(jk_x x+jk_y y)\,dxdy \tag{6}$$

$$F_{VV}(-k_x,0)+F_{VV}(k_x,0)=\frac{2\sin^2\theta(1+R_{\parallel})^2}{\cos\theta}\cdot\left[(1-\frac{1}{\varepsilon_r})+\frac{\mu_r\varepsilon_r-\sin^2\theta-\varepsilon_r\cos^2\theta}{\varepsilon_r{}^2\cos^2\theta}\right] \tag{7}$$

$$F_{HH}(-k_x,0)+F_{HH}(k_x,0)=-\frac{2\sin^2\theta(1+R_{\perp})^2}{\cos\theta}\cdot\left[(1-\frac{1}{\mu_r})+\frac{\mu_r\varepsilon_r-\sin^2\theta-\mu_r\cos^2\theta}{\mu_r{}^2\cos^2\theta}\right] \tag{8}$$

Where k is the radar wave number, k_z is equal to $k\cos\theta$, θ is the radar angle of incidence, σ is the standard deviation of surface height, ε_r is the relative permittivity (relative dielectric constant) of the soil, μ_r is the relative permeability and $R_{\parallel}$ and $R_{\perp}$ are the vertically and horizontally polarized Fresnel reflection coefficient, respectively. pq is the co-polarization or cross-polarization (HH, VV and HV). $W^n(k_x, k_y)$ is the Fourier transform of the nth power of the surface correlation function. The surface correlation function $\rho(x, y)$ with exponential distribution is given by ρ(x,y) = exp $\{-(|x|+|y|)/L\}$ and surface correlation with Gaussian distribution is given by ρ(x,y) = $\exp = \{-(x^2+y^2)/L^2\}$. Here, L is correlation length. In this study both of these correlation functions were examined and the results of exponential auto correlation function were much better than Gaussian auto correlation function. There for we use exponential auto correlation function in this study.

3.2. The semi-empirical Dubois model

Dubois et al. (1995) suggested a semi-empirical approach for modelling σ^0_{HH} and σ^0_{VV} radar backscatter coefficients, using scatterometer data. The expressions for σ^0_{HH} and σ^0_{VV} involve the angle of incidence (θ), the dielectric constant (ε_r), the standard deviation of surface height (h_{rms}) and the wavelength (λ= 2π/k, in cm):

$$\sigma^0_{HH} = 10^{-2.75}\left(\frac{\cos^{1.5}\theta}{\sin^5\theta}\right)10^{0.028.\varepsilon_r.\tan\theta}(k.h_{rms}.\sin\theta)^{1.4}\lambda^{0.7} \quad (9)$$

$$\sigma^0_{VV} = 10^{-2.35}\left(\frac{\cos^3\theta}{\sin^3\theta}\right)10^{0.046.\varepsilon_r.\tan\theta}(k.h_{rms}.\sin\theta)^{1.1}\lambda^{0.7} \quad (10)$$

The algorithm is optimized for bare soils with $k.h_{rms} \le 2.5$, $mv \le 35\%$ and $\theta \ge 30°$ (Dubois et al. 1995).

3.3. The semi-empirical Oh model

Oh (Oh et al. 1992, 1994, 2002, Oh 2004) developed a semi-empirical backscattering model based on theoretical models, scatterometer measurements and airborne SAR observations over a wide variety of bare soil surfaces. The model relates the co-polarized ratio p = $\sigma^0_{HH} / \sigma^0_{VV}$ and the cross-polarized ratio q = $\sigma^0_{HV} / \sigma^0_{VV}$ to incident angle (θ), wave number (k), standard deviation of surface height (h_{rms}) and volumetric soil moisture (mv). The initial version of the Oh model was presented by Oh et al. (1992):

$$p = \sigma^0_{HH} / \sigma^0_{VV} = [1 - (\frac{\theta}{90°})^{1/3\Gamma_0}\, e^{-k.h_{rms}}]^2 \quad (12)$$

$$q = \sigma^0_{HV} / \sigma^0_{VV} = 0.23\sqrt{\Gamma_0}(1 - e^{-k.h_{rms}}) \quad (13)$$

Where

$$\Gamma_0 = \left|\frac{1-\sqrt{\varepsilon_r}}{1+\sqrt{\varepsilon_r}}\right|^2 \quad (14)$$

A new expression for q was proposed by Oh et al. (1994) to incorporate the effect of the incidence angle:

$$q = \sigma^0_{HV} / \sigma^0_{VV} = 0.25\sqrt{\Gamma_0}(0.1 + \sin^{0.9}\theta)(1 - e^{-[1.4-1.6\Gamma_0]k.h_{rms}}) \quad (15)$$

The expressions for p and q were again modified in 2002, and an expression was proposed for the cross-polarized backscatter coefficient (Oh et al. 2002):

$$p = 1 - (\frac{\theta}{90°})^{0.35.mv^{-0.65}} e^{-0.4(k.h_{rms})^{1.4}} \quad (16)$$

$$q = 0.1(\frac{h_{rms}}{L} + \sin 1.3\theta)^{1.2}(1 - e^{-0.9(k.h_{rms})^{0.8}}) \quad (17)$$

$$\sigma^0_{HV} = 0.11 mv^{0.7}\cos^{2.2}\theta(1 - e^{-0.32(k.h_{rms})^{1.8}}) \quad (18)$$

Given that the measurement of the correlation length is not exact (Oh and Kay 1998, Baghdadi et al. 2000) and that the ratio q is insensitive to the roughness parameter (rms/L), Oh (2004) proposed a new formulation for q that ignores the correlation length:

$$q = 0.095(0.13 + \sin 1.5\theta)^{1.4}(1 - e^{-1.3(k.h_{rms})0.9})$$

The algorithm is optimized for bare soils with $0.1 \le k.h_{rms} \le 2.5$, $9\% \le mv \le 31\%$ and $10° \le \theta \le 70°$ (Oh et al. 1994).

4. Comparison between modeled and measured data

The performance of each scattering model is evaluated using the statistical indexes suggested by Willmott (1992):

Root mean square error

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \quad (19)$$

Bias

$$Bias = \frac{1}{N}(O_i - P_i) \quad (20)$$

Here P is the model-predicted variable, O the observed variable and N the data number.

Figures 2a, b and c present the IEM model results in L and C band for HH and VV polarization and figures 2d, e and f present the Dubois model results in L and C band for back scatter coefficients σ^0_{HH} and σ^0_{VV} , and finally figures 2g, h, i and j present the Oh model results in L and C band for back scatter coefficients p = $\sigma^0_{HH} / \sigma^0_{VV}$, q = $\sigma^0_{HV} / \sigma^0_{VV}$ and σ^0_{HV} from 1992, 1994, 2002 and 2004 version.

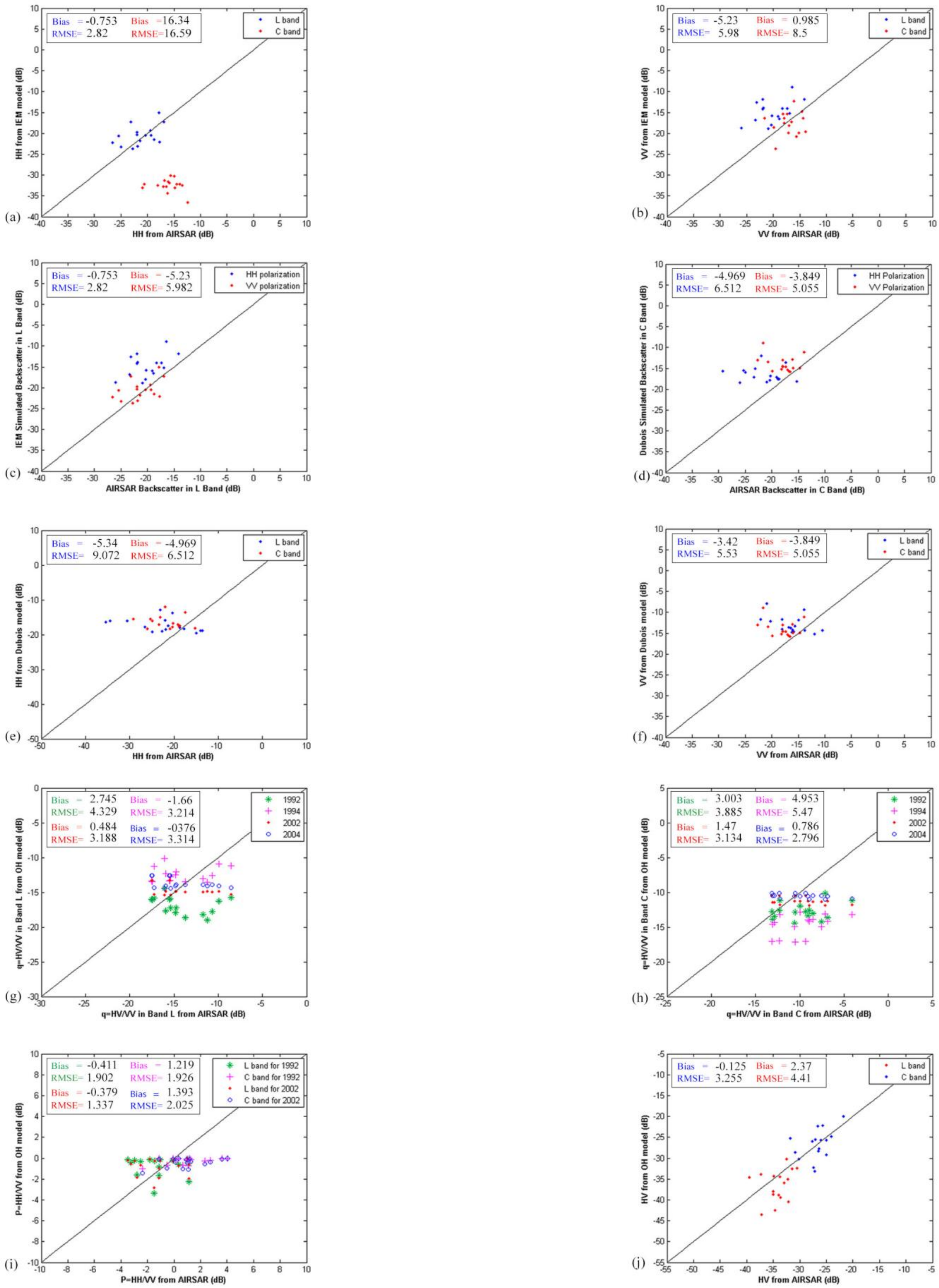

Figure 2. a, b and c present the IEM model results in L and C band for HH and VV polarization and d, e and f present the Dubois model results in L and C band for back scatter coefficients σ_{HH}^{0} and σ_{VV}^{0} , and finally g, i and j present the Oh model results in L and C band for back scatter coefficients p, q and σ_{HV}^{0} from 1992, 1994, 2002 and 2004 version.

5. Discussion

5.1. Evaluation of the IEM model

In this study the backscatter coefficients of IEM model were simulated in L and C band and HH and VV polarization over three different vegetation canopy covers and three different soil depths. The results obtained show that IEM model is frequently tended to under-estimate the radar signal in C band (Figure 2a , b) and over-estimate it in L band (Figure 2a, b). Figure 2b shows that errors obtained in L band are much smaller than those obtained in C band (RMSE = 5.982 dB for L band and 8.501 dB for C band) and also figure 2c shows that in L band the HH backscatter results were more precise than VV backscatter (RMSE = 2.82 dB for HH and 5.982 dB for VV). Examination of this model in three different soil depth (0-3 cm ,3-6 cm and 0-6 cm) shows that the best results are related to 0-3 cm soil depth followed by 0-6 cm soil depth. The 3-6 cm soil depth results shows the weakest correlation. As an example for L band and VV polarization in different soil depths the RMSE values are equal to 5.982 dB for 0-3 cm, 7.007 dB for 0-6 cm and 7.859 dB for 3-6 cm. The results of C band in different soil depth shows that this band cannot simulate backscatter in depth more than 0-3 cm due to its small wavelength and in depths such as 0-6 cm or 3-6 cm errors are too large. (RMSE = 8.501 dB in 0-3 cm, 53.803 dB in 3-6 cm and 48.953 dB in 06 cm). This model also examined in different vegetation canopy covers and for this purpose Normal Differences Vegetation Index (NDVI) was used. All backscatters in L and C band were simulated in three different NDVI (NDVI ≤ 0.2, 0.2 < NDVI ≤ 0.4 and 0.4 < NDVI ≤ 0.6). The results obtained show that in both bands and all backscatters the best results are related to bare soil area with NDVI ≤ 0.2 and after that for 0.2 < NDVI ≤ 0.4 and finally 0.4 < NDVI ≤ 0.6. For example in L band and HH polarization the rms error is about 5.982 dB for NDVI ≤ 0.2, 6.253 dB for 0.2 < NDVI ≤ 0.4 and 8.185 dB for 0.4 < NDVI ≤ 0.6. These results have been expected since in the IEM model there is no parameter to model the impact of vegetation cover. Therefore in order to estimate soil moisture with this model in area with vegetation cover propose that impact of vegetation cover omit from the radar backscatter before suing this model.

5.2. Evaluation of the Dubois model

In this study the backscatter coefficients of Dubois model namely σ^0_{HH} and σ^0_{VV} were simulated in L and C band over two different vegetation canopy covers and three different soil depths. Generally speaking, the Dubois model tends to over-estimate the radar signal in all bands and backscatters (figure 2(d), (e) and (f)). Results obtained show that in C band the Dubois model agrees closely to the measured data than L band and also the errors obtained in VV polarization are smaller than those observed in HH polarization in both bands (Figure 2(e) and (f)). Thus the best results obtained in C band and VV polarization (RMSE = 5.055 dB). Examination of this model in three different soil depth (0-3 cm, 3-6 cm and 0-6 cm) shows the same behaviour as IEM model that the best results are related to 0-3 cm and then 0-6 cm and finally 3-6 cm. (RMSE for C band and VV polarization in 0-3 cm = 5.055 dB, 0-6 cm = 5.826 dB and 3-6 cm = 6.563 dB). This model was suggested by Dubois et al. (1995) for bare surface however they suggested that the inversion of their algorithm could be applied to surfaces with NDVI as high as 0.4.(Dubois et al. (1995)). Therefor in this research the Dubois model was examined under two vegetation canopy cover. The results obtained show that the both HH and VV backscatters in C band and the VV backscatter in L band were simulated more precisely in bare soil area with NDVI ≤ 0.2 that in area with moderate vegetation cover 0.2 < NDVI ≤ 0.4.However the HH backscatter in L band was simulated more precisely in area with 0.2 < NDVI ≤ 0.4 than in bare soil area with NDVI ≤ 0.2.

5.3. Evaluation of the OH model

In this study the all backscatter coefficients of OH model which had been developed since 1992 to 2002 were simulated in L and C band over three different soil depths. The Oh model tends to over-estimate the radar signal in C bands except for backscatter coefficient σ^0_{HV} (Figure 2(h) and (i)) but in L band OH model mostly tends to under-estimate the radar signal except for ratio q from the 1994 and 2002 version (Figure 2(g) and (i)). Figure 2(i) shows that ratio p from the 1992 and 2002 version can simulate radar signal in L band better than in C band (RMSE = 1.337059418 dB for ratio p in L band and 2.025981843 dB in C band), and the best result of ratio p obtained in L band and from the 2002 version. However in C band ratio p is slightly better in the 1992 version than the 2002 version (Figure 2(i)). Other results for ratio q illustrate that this ratio can estimate radar backscatter mostly better in C band rather than L band (Figure 2(g), (h)). For example all cross-polarized ratio q results for 1992, 2002 and 2004 version in C band were more precise than those in L band. The results obtained from the backscatter coefficient σ^0_{HV} show that this coefficient was over-estimated by the Oh model in L band and under-estimated by this model in C band (Figure 2(j)). More over the errors obtained for this coefficient in C band are smaller than those obtained in L band (RMSE = 3.255276629 dB in C band and 4.417182609 dB in L band). Examination of this model in three different soil depths (0-3 cm ,3-6 cm and 0-6 cm) shows that the best results mostly are related to 0-3 cm soil depth and after that to 0-6 cm soil depth and finally to the 3-6 cm soil depth However, the ratio q from the 1994 ratio in just C band show completely different behaviour. For this ratios the best result are related to 3-6 cm soil depth, after that to the 0-6 cm soil depth and finally to the 0-3 cm soil depth. However our data base is not big enough to for a detailed study of the behaviour of this error.

6. Conclusion

The objective of this article is to evaluate the semi-empirical models of Oh and Dubois and the theoretical integral equation model (IEM) using L and C-bands with ground measurements over vegetation cover and bare soli in agricultural environments and different soil depths. The results show that Dubois model tend to over-estimate the radar response in both bands but IEM model and Oh model frequently over-estimate the radar response in L band and under-estimate them in C band. As mentioned earlier, by examination of models in different soil depths and vegetation canopy covers, best results obtained in 0-3 cm depths and area with NDVI ≤ 0.2.

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