Assessment of Different Backscattering Models for Bare Soil Surface Parameters Estimation from SAR Data in band C, L and P

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Abstract
Synthetic Aperture Radar (SAR) is the most widely used sensor for retrieving soil surface parameters. This study was performed in two steps. In the first step, estimated backscattering coefficients using three models, Oh, Dubois, and IEM, in three bands of P, L, and C and two polarizations of HH and VV were compared with those extracted from SAR data acquire from AIRSAR over LWREW experimental site located in southwestern Oklahoma with a sub-humid climate. The results showed that the Oh model in band C had the best accuracy in both polarizations (RMSE_HH=1.48 and RMSE_VV=1.1). Dubois and IEM models were appropriately accurate in band L; however, both were less accurate compared with the Oh model in band C. In the second step, ground truth measurements of soil roughness, dielectric constant, and correlation length were compared with the corresponding results of inversion backscattering models. Based on the findings, it was concluded that IEM performed better at estimating soil roughness with RMSE=0.37, while Oh more accurately assessed dielectric constant in all three bands and at depths of 0-3 cm and 3-6 cm. All results confirmed that band P was not appropriate for retrieving soil surface parameters using backscattering models compared with the bands of C and L.

Keywords: SAR remote sensing, backscattering model, soil moisture, soil roughness, correlation length.

Introduction
Soil surface parameters are key in many environmental studies in fields such as global water and hydrology, energy cycles, agriculture, and geology [Ulaby et al., 1981; Koster et al., 2004; Paloscia et al., 2012]. The development of various algorithms for estimating soil surface parameters, such as soil moisture and soil roughness, could be useful in different sciences.
Synthetic Aperture Radar (SAR) is an active microwave sensor with the capability of acquiring data under almost any meteorological conditions and without an external source
of illumination. The potential of using SAR data to monitor the earth’s surface has been demonstrated. This technology has been used for approximately 30 years to measure soil surface parameters such as roughness and moisture [Wagner and Pathe, 2005; Balenzano et al., 2013]. The launching of various SAR sensors with appropriate spatial resolution like SMAP and different polarizations in different frequencies provides a great opportunity to research the production of more accurate models for estimating soil surface parameters. For instance, SAR provides the capability of assessing soil moisture in deeper depths compared to optical remote sensing [Topp et al., 1980; Walker, 1999]. The basis of microwave remote sensing for soil moisture assessment is measuring dielectric constant in wet and dry soil and the relation between Fresnel reflection coefficient and dielectric constant [Jackson et al., 1982].

The relation between soil surface parameters and SAR signals is usually defined using backscattering models [Sahebi et al., 2002]. These models are classified into three groups [Walker et al., 1999]: 1) theoretical, such as Integral Equation Model (IEM) [Fung et al., 1992]; 2) empirical, such as Attema and Ulaby [1978], Shi et al. [1997] and Sahebi et al. [2003]; 3) semi-empirical, such as Dubois et al. [1995] and Oh et al. [1992]. They are used to model the behavior of signals in reaction to soil surface; however, the inverse of these models can be applied to estimating soil surface parameters. In fact, inverse methods retrieve soil surface parameters using backscattering models. Among numerous backscattering models, the most widely applied are IEM, a theoretical model, and two semi-empirical models, the Dubois and the Oh models. Each model’s operation process is based on two main factors: sensor and soil parameters. The sensor parameters are represented by variations in signal backscatter as a function of wavelength (λ), incidence angle (θ), and polarization (p); target parameters are related to surface parameters, such as roughness and dielectric constant.

To estimate soil surface parameters, different backscattering models have been introduced by Ulaby et al. [1981], Oh et al. [1992], Fung et al. [1992], Shi et al. [1997], Sahebi et al. [2002], and other researchers. Semi-empirical models provide relatively simple relationships between surface properties and SAR signals; however, they rely on parameters which are often site specific and therefore valid only for specific soil conditions. Conversely, theoretical approaches based on electromagnetic scattering theory, even though they provide site-independent relationships, are mathematically more complex and involve a heavier computational burden [Panciera et al., 2014]. Since this study applied the three models of IEM, Oh and Dubois to estimate soil surface parameters, a brief description of each of these models is provided below.

IEM is a theoretical (physical) model based radiative transfer model developed by combining the Kirchhoff models and Small Perturbation Model (SPM) to make it applicable in different roughness conditions and spatially independent. Oh et al. [1992] introduced their semi-empirical model based on laboratory experimental results. The Oh model relates backscattering coefficients with soil moisture and roughness. Dubois et al. [1995] offered the Dubois semi-empirical model only for co-polarized backscattering to operate in 6 frequencies ranging from 2.5 to 11 GHz. It is, however, more sensitive to noise and more accurate than cross-polarized backscattering; furthermore, it calibrates more easily. In this regard, Sikdar et al. [2004] and Neusch and Sties [1999] have reported more accurate results in dry lands with sparse vegetation cover. Findings by Alvarez-Mozos et al. [2007] showed that using multi-polarized data, dielectric constant and
surface roughness could be estimated without in-situ measurements. Sahebi and Angles [2010] compared the Geometrical Optics Model (GOM), Physical Optic Model (POM), Oh Model, and Modified Dubois Model (MDM) using multi-angular RADARSAT and reported that MDM is the most versatile model for retrieving soil surface parameters. They also indicated that multi-angular data are more effective than multi-polarization data and that IEM is the most accurate model compared with the others [Sahebi et al., 2004].

The current study was performed in two steps. In the first step, the Oh, Dubois, and IEM backscattering models were used in bands P, L, and C, to compare the evaluated backscattering coefficients of the models with those obtained from SAR data in HH and VV polarizations. In the second step, the rms height (vertical variations of soil roughness), dielectric constant, and correlation length (horizontal variations of soil roughness) of ground truth were compared with the corresponding results of the inversion backscattering models.

**Method and materials**

**Study area and field data**
The Little Washita Experimental Watershed (LWREW) located in southwestern Oklahoma in the Southern Great Plains region of the USA was chosen for the current study. The covered area was about 611 km$^2$ (Fig. 1). This site is well instrumented for surface soil moisture, hydrology, and meteorology research. A sub-humid climate is generally defined for this region, and average annual rainfall is 75 cm. The topography is moderately rolling with a maximum elevation of less than 200 m. Soils include a wide range of textures with large regions of both coarse and fine textures. Land use in the watershed is dominated by rangeland and pasture (63%) with significant areas of winter wheat and other crops concentrated in the floodplain and western portions of the watershed area. This kind of climate, land cover and soil surface conditions can be found in different parts of the USA and other countries. Therefore, it is assumed the results of the work can be valid for the same situations.

![Figure 1 - Location of the study area.](image)
In-situ measured data used in this work came from Soil Moisture Experiments (SMEX03) collected on 3rd July 2003 and included gravimetric soil moisture, volumetric soil moisture, bulk density, surface and soil temperature, surface roughness data, and dielectric constant. Surface roughness included root mean square height (rms), correlation length (l), and correlation length function (f(L)). For each regional study area, surface roughness conditions were photographed using a grid board. Roughness photographs were then digitized in order to derive surface roughness calculations. Soil dielectric constants measured with impedance probes (ThetaProbes) were used in computing volumetric soil moisture. To convert soil moisture to dielectric constants the empirical method presented by Hallikainen [Hallikainen et al., 1985] was considered. The sampling process was performed on sites in approximately one-quarter sections, 0.8 km by 0.8 km in size. Figure 2 illustrates the sampling locations within the one-quarter section sites. In this study, the LWREW data with 13 site and 54 sampling points were used [SMEX03].

**Figure 2 - a) LWREW field sampling design; b) Ground photo from field work.**

**AIRSAR data and preparation**

SMEX03 uses polarimetric (POLSAR) data. In POLSAR mode, fully polarimetric data are acquired at all three frequencies of C, L, and P bands. Fully polarimetric means that radar waves are alternatively transmitted in Horizontal (H) and Vertical (V) polarization, while every pulse is received in both H and V polarizations. Therefore, four combinations, HH, HV, VV, and VH, are available.

The Airborne Synthetic Aperture Radar (AIRSAR) images used in this study were acquired on July 3rd, 2003. AIRSAR data were in Stokes matrix format with a pixel size of 6.6 m in range direction and 9.26 m in azimuth direction. Basic parameters of the AIRSAR sensor are listed in Table 1.

For image pre-processing, the synthesized and decompressed procedures were performed first to derive the backscattering coefficients ($\sigma^0$ in dB). By doing so, the radar data were available in HH, HV, VV, and TP (Total Power) polarizations in P, L, and C frequencies. To use the information obtained from SMEX, a resampling process was carried out to convert the 9.2 m spatial resolution to a 6.7 m grid. Finally, for geo-referencing, Digital Ortho-photo Quadrangles (DOQs) with 1 m pixel size were used to correct AIRSAR images. Forty points distributed throughout the scene were used, and 0.5 pixel (3.3 m) RMSE was obtained for the image.
Table 1 - AIRSAR parameters.

| Channel                  | C    | L    | P    |
|--------------------------|------|------|------|
| Frequency (GHz)          | 5.29875 | 1.2375 | 0.4275 |
| Incidence Angles         | 0° - 75° (theoretical, in practice 20° - 70°) |
| Altitude (km)            | 8    |
| Bandwidth (MHz)          | 20   |
| Slant Range Resolution (m)| 6.6621 |
| Azimuth Range Resolution (m)| 9.2592 |

**Method**

This research was realized in two steps. To assess the results, the statistical parameters of R-Square ($R^2$), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were used. It should be considered that the results depended on the accuracy of in-situ field data and environmental conditions. It should be noted that for each model there are some restrictions to use. For each model there are some validity range which are presented in different researches such as Dubois et al. [1995], Ulaby et al. [1981], Sahebi et al. [2002], and Sahebi et al. [2010].

**Comparison between backscattering coefficients**

In the first step of this study, using the Oh, Dubois, and IEM backscattering models in the three bands of P, L, and C, the evaluated backscattering coefficients obtained from models were compared with the same parameters extracted from SAR images in HH and VV polarizations. Then the influence of soil surface parameters on each backscatter coefficient was examined. Efforts were made to choose the most accurate model for estimating soil surface parameters. For the Oh and Dubois models, dielectric constant and roughness were used as input parameters, and for IEM these two parameters plus coefficient length were applied to estimate backscattering coefficients. All input data as model parameters were obtained from image and in-situ measured data.

**Soil surface parameters**

Soil surface parameters are usually retrieved from inverse backscattering models; however, it is important to note whether the models could be inversed or not. To inverse the IEM model, presented methods by Bindlish and Barros [2000] based on multi-frequency configuration were used. This method applies adjustments for the estimation of soil surface parameters. The adjustment method, an iterative method similar to the Newton-Raphson, is used in the retrieval algorithm to resolve the inverse equations. As the inverse problem is over-constrained [Twomey, 1977], adjustment is appropriate. Because the signal-to-noise ratio for the retrieved variable is a function of data noise and the performance of the forward model (for example IEM), it is one of the fundamental requirements of this method [Bindlish and Barros, 2000].
To evaluate dielectric constant and roughness using the DuBois model, the inverse model was used [Sahebi and Angles, 2010]. These two parameters were also calculated using the Oh model and iteration [Oh et al., 1992]. To be more precise, initial values were considered and iterated approximately 30 times.

**Results and discussion**

In the first part of this study, the coefficients of backscattering from models and images were compared; then, the results of each model were individually analyzed. In the second step, the parameters of soil surface were shown separately.

**Comparison of modeled backscattering coefficients and SAR backscattering coefficients**

Figure 3 shows the comparison of backscattering coefficients calculated from AIRSAR data and those modeled values of IEM, Oh, and DuBois in HH and VV polarizations in band C. Based on Figures 3a and 3e, it can be concluded that Oh model had the best accuracy in both HH and VV polarizations with RMSE values equivalent to 1.48 dB and 1.1 dB, respectively. It should be noted that these results were predictable, because this model was defined based on band C. Another result was that IEM seemed to underestimate the radar signal in both HH and VV polarizations, whereas the correlation between measured and simulated data were almost lower in the HH polarization ($R^2=0.0002$). Figures 3b and 3f show that none of the three models were dependent on incidence angle in $\theta \geq 50^\circ$ in both HH and VV polarizations. IEM considerably overestimated the radar signal in $rms \geq 1 cm$ in both polarizations (Figs. 3c and 3g).

![Figure 3](image-url)  
*(Continued on the next page)* - AIRSAR backscattering coefficients versus modeled values of backscattering coefficients using IEM, Oh and DuBois in HH and VV polarization in band C.
Figure 3 (Continued from preceding page) - AIRSAR backscattering coefficients versus modelled values of backscattering coefficients using IEM, Oh and Dubois in HH and VV polarization in band C.
Figure 4 shows the results for IEM, Oh, and Dubois modeled backscattering coefficients and the backscattering coefficients obtained from AIRSAR data in band L and HH and VV polarizations. Although Oh achieved the best accuracy in band C, according to Figure 4a and 4e, it showed underestimation in band L in both polarizations. Generally, the Dubois model seems to underestimate the radar signal by about MAE=2.58 dB in HH polarization, whereas the MAE between observed and estimated data are approximately null in VV polarization. In HH polarization, all three models were independent of dielectric constant in $\varepsilon > 4$ (Fig. 4d).

Figure 4 (Continued on the next page) - AIRSAR backscattering coefficients versus modelled values of backscattering coefficients using IEM, Oh and Dubois in HH and VV polarization in band L.
Figure 4 (Continued from preceding page) - AIRSAR backscattering coefficients versus modelled values of backscattering coefficients using IEM, Oh and Dubois in HH and VV polarization in band L.

Figure 5 depicts those results of Figure 3 and Figure 4 in band P. Acceptable results were not expected in this band due to its wavelength. Analyses of Figure 5a and 5e show that, although Dubois model underestimated SAR signals in HH polarization in most backscatters, it was more accurate than the other two models. IEM achieved acceptable results in VV polarization with RMSE=2.45 db. It was concluded that the Oh-estimated backscattering coefficient was not accordant with radar signal backscattering in either HH ($R^2=0.0026$) or VV ($R^2=0.0689$) polarization. All results regarding soil surface roughness, dielectric constant, and incidence angle confirm that band P is not appropriate.
Figure 5 (Continued on the next page) - AIRSAR backscattering coefficients versus modelled values of backscattering coefficients using IEM, Oh and Dubois in HH and VV polarization in band L.
Table 2 - Statistical parameters calculated using three models of Oh, Dubois and IEM in three bands of C, L and P in HH and VV polarizations for backscattering comparison.

|       | C |     |     | L |     |     | P |     |     |
|-------|---|-----|-----|---|-----|-----|---|-----|-----|
| RMSE  |   |     |     |   |     |     |   |     |     |
| HH    | 1.4761 | 2.0245 | 2.3845 | 2.022 | 1.6235 | 1.7024 | 3.1417 | 2.1956 | 2.6919 |
| VV    | 1.0953 | 1.8443 | 2.2161 | 1.846 | 1.5495 | 1.9055 | 3.6393 | 2.4965 | 2.4534 |
| R²    | 0.012 | 0.0234 | 0.0002 | 0.0373 | 0.1803 | 0.3537 | 0.0026 | 0.1426 | 0.0016 |
| MAE   | 2.1352 | 4.0167 | 5.5720 | 4.0066 | 2.5830 | 2.8402 | 9.6730 | 4.7241 | 7.1015 |
|       | 1.1756 | 3.3334 | 4.8128 | 3.3394 | 2.3531 | 3.5583 | 12.962 | 6.1001 | 5.8909 |

**Estimation of soil surface parameters**

In this section of the study, soil surface parameters were estimated using Oh, Dubois, and IEM models and then compared with in-situ data. Results from the Oh and Dubois models showed separately in each band, but IEM results simultaneously showed all bands.

**Root mean square**

Figure 6 shows the correlation between the in-situ measured soil roughness data and the modeled soil surface roughness by the adjustment method with IEM and the inverse of
Dubois and Oh models. As can be seen, there is a strong correlation ($R^2=0.66$) between these variables in IEM, compared with the other models, because there were three degrees of freedom and the variables were independent in this model. It should be considered that Dubois model achieved appropriate results in band L with $R^2=0.63$ compared with bands P ($R^2=0.18$) and C ($R^2=0.45$). From Figure 6, it can be easily concluded that Oh had the worst accuracy in all three bands for assessing soil surface roughness. This result may be due to the structure of the Oh model and its coefficients for $rms$.

![Figure 6](image)(a) (b) (c)

**Figure 6** - The correlation between soil roughness obtained by Oh, Dubois and IEM and those of in-situ measured data in bands of P, L and C.

For the Oh and IEM models, three different polarizations of HH, VV, and HV were used for the assessment of soil roughness; however, for Dubois model, the data in two copolarizations of HH and VV were used. Table 3 shows the results.
### Table 3 - Statistical parameters calculated using three models of Oh, Dubois and IEM in three bands of C, L and P for soil surface roughness.

|       | Oh          | Dubois      | IEM         |
|-------|-------------|-------------|-------------|
|       | C           | L           | P           | C           | L           | P           | C           | L           | P           |
| RMSE  | 1.0929      | 1.1908      | 0.9884      | 0.7694      | 0.4807      | 0.7046      | 0.3719      |
| $R^2$ | 0.0207      | 0.0386      | 0.022       | 0.4481      | 0.6277      | 0.1825      | 0.6561      |
| MAE   | 1.1668      | 1.3851      | 0.9505      | 0.5785      | 0.2261      | 0.4856      | 0.1344      |

### Dielectric constant

Figure 7 illustrates the correlation between the measured dielectric constant in depth of 0-3 cm and 3-6 cm and the estimated dielectric constant using IEM, Oh, and Dubois in three bands. Analyses of this figure showed that Oh was more accurate for the estimation of dielectric constant in all three bands at 0-3 cm ($C_{RMSE}=1.07$, $L_{RMSE}=1.06$, $P_{RMSE}=1.06$), compared with 3-6 cm ($C_{RMSE}=1.29$, $L_{RMSE}=1.26$, $P_{RMSE}=1.26$). The Dubois model overestimated $\varepsilon$ obtained from radar measurements in L and P bands and underestimated it in band C. Statistical analysis of IEM results showed that the estimated dielectric constant was more accordant to field measurements at 0-3 cm. Examination of all results showed the accuracy of all three models was better in the $0 < \varepsilon < 5$ interval.

Figure 7 (Continued on the next page) - The correlation between estimated and in-situ measured dielectric constant in P, L and C bands in the depths of 0-3 cm (a, b and c) and 3-6cm (d, e and f).
Table 4 shows the results for estimating dielectric constant using the Oh, Dubois, and IEM models in three various bands at depths of 0-3 cm.

**Table 4 - Statistical parameters calculated using three models of Oh, Dubois and IEM in three bands of C, L and P for estimation of dielectric constant in 0-3 cm.**

|       | Oh | Dubois | IEM  |
|-------|----|--------|------|
| 0-3 cm|    |        |      |
| RMSE  | 1.0706 | 1.0623 | 1.0623 | 1.6486 | 2.5086 | 3.0349 | 1.3469 | 1.2514 | 1.2514 |
| $R^2$ | 0.4443 | 0.392 | 0.392 | 0.0386 | 0.0022 | 0.0003 | 0.0737 | 0.181  | 0.181  |
| MAE   | 1.1233 | 1.1058 | 1.1058 | 2.6589 | 6.1593 | 8.8696 | 1.7638 | 1.5224 | 1.5224 |
Table 5 shows the results for estimating dielectric constant using the Oh, Dubois, and IEM methods in three various bands at depths of 3-6 cm.

Table 5 - Statistical parameters calculated using three models of Oh, Dubois and IEM in three bands of C, L and P for estimation of dielectric constant in 3-6 cm.

|         | Oh       | Dubois   | IEM      |
|---------|----------|----------|----------|
|         | C        | L        | P        | C        | L        | P        | C        | L        | P        |
| RMSE    | 1.2903   | 1.2604   | 1.2604   | 1.8769   | 2.246    | 2.808    | 1.6002   | 1.5992   | 1.5992   |
| $R^2$   | 0.5345   | 0.5117   | 0.5117   | 0.0033   | 0.0061   | 0.0004   | 0.0064   | 0.037    | 0.037    |
| MAE     | 1.6316   | 1.5569   | 1.5569   | 3.4463   | 4.9349   | 7.3472   | 2.4896   | 2.4865   | 2.4865   |

Correlation length
In another approach, IEM was used to estimate correlation length in three bands of P, L, and C with two different polarizations of HH and VV. Since the correlation length could only be used in IEM, this parameter was assessed by the Bindlish method, and an RMSE of 2.43 was achieved. Figure 8 shows that, although the results tended to underestimate in $4 < \text{rms} < 6$, it was more accurate for $\text{rms} \approx 5$.

Figure 8 - The correlation between IEM modelled correlation length and those of in-situ measured data in the of P, L and C bands.
Conclusion
There are some methods for retrieving soil surface parameters using various backscattering models and different inverse mathematical and physical methods. Considering the background of backscattering models, this study applied the Oh, Dubois, and IEM models in the P, L, and C bands in HH and VV polarizations. The field data were collected by SMEX03 from southwest Oklahoma. The objective of this study was to determine the most accurate model for estimating soil surface parameters. First, backscattering coefficients estimated from the three models in bands P, L, and C and in both HH and VV polarizations were compared with those extracted from the SAR image. The results showed that Oh was the most accurate model in band C in both polarizations with RMSE=1.1. Dubois showed the highest accuracy in band L in both polarizations. In regard to band P, it was concluded that IEM and Dubois had the highest correlations in VV and HH polarizations, respectively. IEM seemed to underestimate the radar signal in band L, possibly because of the correlation between the parameters of this model. It was concluded that as the dielectric constant increases in $\varepsilon > 4$, the dependency of Oh on this parameter will decrease in all bands.

In part two of this research work, soil surface parameters were estimated using inverse Oh, Dubois, and IEM. Based on the results of this part, it can be concluded that IEM, which was the applied adjustment method, was the best model for retrieving soil roughness. A comparison of Oh and Dubois in band L showed that Dubois was more appropriate for estimating soil roughness, while Oh was more accurate in assessing dielectric constant. The results of the second step of this study confirmed that estimates of dielectric constant were more accordant to in-situ measured $\varepsilon$ at depths of 0-3 cm, except that of Dubois in band L.

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