Calibrated Integral Equation Model for Bare Soil Moisture Retrieval of Synthetic Aperture Radar: A Case Study in Linze County

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Abstract: Soil moisture plays a significant role in surface energy balance and material exchange. Synthetic aperture radar (SAR) provides a promising data source to monitor soil moisture. However, soil surface roughness is a key difficulty in bare soil moisture retrieval. To reduce the measurement error of the correlation length and improve the inversion accuracy, we used the surface roughness \((H_{rms}, \text{root mean surface height})\) and empirical correlation length \(l_{opt}\) as proposed by Baghdadi to introduce analytical equations of the backscattering coefficient using the calibrated integral equation model (CIEM). This empirical model was developed based on analytical equations to invert soil moisture for \(H_{rms}\) between 0.5 and 4 cm. Experimental results demonstrated that when the incidence angle varied from 33.5° to 26.3°, \(R^2\) of the retrieved and measured soil moisture decreased from 0.67 to 0.57, and RMSE increased from 2.53% to 5.4%. Similarly, when the incidence angle varied from 33.5° to 26.3°, \(R^2\) of the retrieved and measured \(H_{rms}\) decreased from 0.64 to 0.51, and RMSE increased from 0.33 to 0.4 cm. Therefore, it is feasible to use the empirical model to invert soil moisture and surface roughness for bare soils. In the inversion of the soil moisture and \(H_{rms}\), using \(H_{rms}\) and the empirical correlation length \(l_{opt}\) as the roughness parameters in the simulations is sufficient. The empirical model has favorable validity when the incidence angle is set to 33.5° and 26.3° at the C-band.

Keywords: synthetic aperture radar (SAR); calibrated integral equation model (CIEM); soil moisture retrieval; surface roughness \((H_{rms})\); empirical correlation length \((l_{opt})\)

1. Introduction

Soil moisture is a crucial state variable in the fields of hydrology, climatology, ecology, and agriculture [1–4]. With the development of remote sensing (RS) technology, large-scale monitoring of soil moisture has become a reality without expensive in situ monitoring networks. As an active microwave that can monitor soil moisture at a spatial resolution of meters to tens of meters under almost all weather conditions, synthetic aperture radar (SAR) is a promising data source to monitor soil moisture with relatively high prediction accuracy [5,6]. In recent years, as SAR satellite sensors develop from the earlier Seasat, ERS-1/2, JERS-1, RADARSAT-1 and other single-polarization space-borne sensors to the more recent ENVISAT/ASAR, SIR-C/X-SAR, ALOS/PALSAR, Sentinel-1, RADARSAT-2, TerraSAR-X, Cosmo-Skymed, GF-3, ALOS-2 multiband, and multipolarization satellite sensors, SAR has been widely used for soil moisture inversion [7–11].

According to the land cover class, the methods of soil moisture inversion using SAR data can be classified into two types: methods applied to bare soils [9–11] and methods for soils covered by vegetation [12–17]. For soil moisture inversion of soils with vegetation coverage, the key question
is how to eliminate the effect of vegetation coverage on the backscattering coefficient. MIMICS and water-cloud models are currently used to describe the backscattering. Because of the complexity of the MIMICS model, the use of the water-cloud model became common [18,19]. El Hajj [20] developed an inversion approach to estimate surface soil moisture using sentinel-1/2 data based on the calibration of the water-cloud model. For soil moisture inversion of bare soil, the main problem is how to handle the soil surface roughness. Unsuccessful roughness parameterization has become the main source of error that affects the accuracy of soil moisture inversion. Currently, there are four conventional methods to parameterize the surface roughness [21]. The first method is change-detection analysis under the assumption of constant roughness. Rahman et al. [22] offered a solution strategy to estimate soil moisture using multangle radar images without ancillary data. The second method is calibrating soil roughness parameters. Baghdadi et al. (2002) developed a calibrated integral equation model (CIEM), which used the empirical correlation length $l_{opt}$ to replace the correlation length $l$ [23]. The third method is combining the semiempirical relations between the correlation length and root mean square height ($H_{rms}$). Zribi et al. (2014) proposed a new description of soil surface roughness for soil moisture [24]. The fourth method is using prior knowledge of the roughness state. Satalino et al. (2002) used prior information on the surface roughness of a given area to invert soil moisture [25]. There are other alternative approaches to the roughness problem, such as multiscale processes [26,27], two-dimensional surface roughness characterization [28,29], and polarization decomposition data usage [30,31]. There are also radar backscatter models that can correctly model the radar signal for a wide range of soil parameters in bare surface soil [32], which can be physical, semiempirical, or empirical. The most popular physical models are the integral equation model (IEM) [33], an IEM calibrated by Baghdadi, which is called the calibrated integral equation model (CIEM) in this paper [23,34–38], and the advanced integral equation model (AIEM) [39].

This paper intensively exploits the surface roughness by combining the change-detection analysis under the assumption of constant roughness and the calibrating soil roughness parameters. The approach attempts to use the backscattering of VV and VH polarizations and CIEM to invert soil moisture and surface roughness in bare soil. The surface roughness parameter can often be expressed as $H_{rms}$ and the correlation length $l$. Fung has suggested that it is a difficult task to separately estimate the effects of $H_{rms}$ and correlation length $l$ on the backscattering behavior of rough surfaces [33]. Furthermore, Zbiri has indicated that when IEM/AIEM is used to simulate the backscattering characteristics, using only $H_{rms}$ as a roughness parameter in the simulations is not sufficient to derive correct results because the effect of correlation length $l$ on the backscattering coefficient is neglected [40]. In addition, Rahman et al. (2008) suggested that conducting field measurement of roughness may become impractical and expensive when large areas must be covered [22]. Therefore, many researchers [40–43] introduced a roughness parameter $Z_s$ (which is equal to $H_{rms}^2/l$) expressed as the surface roughness to invert soil moisture. However, roughness parameter $Z_s$ adopted correlation length $l$ in their studies. One study showed that the measurement error of correlation length $l$ was much larger than that of $H_{rms}$ in the roughness measurement of the fieldwork [35]. Therefore, how to reduce the error of the correlation length when the soil surface roughness is parameterized has become the major question to answer.

In this paper, the surface roughness defined by $H_{rms}$ and the empirical correlation length $l_{opt}$ as proposed by Baghdadi were used to introduce analytical equations of backscattering coefficient using the CIEM. When the backscatter database was built to propose analytical equations of the backscattering coefficient, many researchers mostly used the IEM and AIEM, whereas CIEM was rarely used [40,41,44,45]. To compare the findings concerning the surface roughness parameterization and model, the related studies were summarized in Table 1.
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Building the soil moisture inversion model, the combined roughness parameter was not used; only $H_{rms}$ and the empirical correlation length $l_{opt}$ were used. Finally, this empirical model was developed based on the analytical equations to invert the soil moisture and surface roughness. The experimental results show that using $H_{rms}$ and the empirical correlation length $l_{opt}$ as the roughness parameters in the simulations is sufficient for the inversion.

2. Study Area and Data

2.1. Study Area

In Figure 1, the study area is located in Linze County in Zhangye, Gansu province, China. The central position is 39.250° N, 100.005° E, and the altitude is 1385 m. The land cover map is obtained from GLC30 [50].

The region is in a temperate drought desert climate zone in the middle reach of Heihe River Basin with a flat terrain, which belongs to the lower plain part of the corridor. The average annual rainfall is 121.5 mm with an annual potential evaporation exceeding 2340 mm. The dry index is 15.9. The average temperature and annual sunshine hours are 7.1 °C and 3045 h, respectively. The ground features are mainly bare land and farmland with a small amount of sparse sedge. There is approximately 16.7% sandy soil, 74.8% sand, and 8.5% clay in the sand texture [46].

![Figure 1. Cont.](image-url)
were made within ±2 h of the ASAR overpasses. The soil texture was analyzed by soil samples. During this period, no precipitation or obvious temperature changes occurred in the experimental area.

The size of the study area is 0.36 × 0.36 km, and there are 49 sample points in this region. The soil samples were collected from the upper 0–5 cm soil layer. Most field measurements of soil moisture were made within ±2 h of the ASAR overpasses. The soil texture was analyzed by soil samples.

The soil moisture content of each sample point was measured by gravimetry. Firstly, the samples were obtained by a cutting-ring method, and the total weight of the soil was obtained using scales and expressed as $G_{\text{wet}}$. Secondly, the soils were dried, and the weight was expressed as $G_{\text{dry}}$. Thirdly, the volume of the cutting ring was provided, which was 50 cm$^3$ and expressed as $V_{\text{soil}}$. Finally, the measured soil volume water content was calculated by the formula $m_v = (G_{\text{wet}} - G_{\text{dry}})/V_{\text{soil}}$. The soil moisture in the field measurements was 13.5–50.7%.

The surface roughness data were measured using needle profilometers, which were 1 m long, and a digital camera. There were 101 needles with a 1-cm sampling interval between needles in the needle profilometers. At each sampling site, two field photographs were taken: along a north–south direction and along an east–west direction. Two roughness profiles were established for each sampling point. Standard deviations of $H_{\text{rms}}$ and correlation length $l$ were calculated using the mean of the autocorrelation function based on these measurements. The $H_{\text{rms}}$ in the field measurements was 0.68–4.08 cm with an average of 1.4 cm, and the correlation length was 53–69 cm. The soil temperature
was obtained by a needle thermometer, and it was observed twice at each sampling point. Detailed data are shown in Table 2.

### Table 2. ASAR images and simultaneous ground-based measurement data.

| Satellite Data Description | Satellite Data | Polarization | Band | Acquisition Date | Incidence Angle (°) |
|-----------------------------|----------------|--------------|------|-------------------|---------------------|
| ENVISAT/ASAR                | VV/VH          | C            | 11 July 2008 | 33.5°              |
| ENVISAT/ASAR                | VV/VH          | C            | 24 May 2008  | 26.3°              |

| Ground Measurements Data | | Min | Max | Average | Observation Time |
|--------------------------|-----|-----|-----|---------|------------------|
| Soil moisture (%)        | 13.5| 34.7| 18.6| 11 July 2008 |
| Soil moisture (%)        | 17.6| 50.7| 24.7| 24 May 2008  |
| Hrms (cm)                | 0.68 | 4.08| 1.4 | 7 June 2008  |
| Correlation length (cm)  | 53   | 69  | 63.2| 7 June 2008  |

### Model Construction

#### 3. Model Construction

##### 3.1. Integral Equation Model and Calibrated Integral Equation Model

The IEM is the most commonly used physical model [54]. In the C-band, the validity domain of IEM [33] covers only a part of the range of roughness values commonly encountered for agricultural surfaces (\( k \times Hrms \leq 3 \) corresponds to \( Hrms \leq 1.11 \) cm\(^{-1} \) in C-band). The IEM describes the relationship between the backscattering coefficient with the characteristics of the sensor (incidence angle, polarization, and radar wavelength) and the soil properties (dielectric constant, \( Hrms \), correlation length, and correlation function) over bare soils in agriculturally bare areas. It can be expressed as follows:

\[
\sigma_0^{pp} = \frac{k^2}{2} \left| f_{pp} \right|^2 e^{-2Hrms^2k^2 \cos^2 \theta} \left( 1 + \sum_{n=1}^{\infty} \frac{(4Hrms^2k^2 \cos^2 \theta)^n}{n!} W^{(n)}(2k \sin \theta, 0) \right) + \frac{k^2}{2} \text{Re}(f_{pp}^*F_{pp}) e^{-2Hrms^2k^2 \cos^2 \theta} \left( 1 + \sum_{n=1}^{\infty} \frac{(4Hrms^2k^2 \cos^2 \theta)^n}{n!} W^{(n)}(2k \sin \theta, 0) \right)
\]

The CIEM is a semiempirical calibration model, which was proposed based on IEM by Baghdadi et al. [35,36]. The proposed CIEM adopts the empirical correlation length \( l_{opt} \) and reduces the number of input soil parameters of the IEM from three to two (\( Hrms \) and \( mv \) only, instead of \( Hrms \), \( l \) and \( mv \)). Correlation length \( l \) as the measured correlation length was replaced by a calibration parameter \( l_{opt} \) included in the CIEM. Calibration parameter \( l_{opt} \) (an empirical correlation length) is computed as a function of the \( Hrms \), radar frequency, incidence angle, and polarization to obtain a better fit between CIEM simulations and radar observations.

The variable \( l_{opt} \) in CIEM is not the input parameter but can be calculated in CIEM. Furthermore, it integrates the true correlation length and the imperfections of the IEM so that the simulated data using the CIEM can be consistent with radar measurement data.

For C-band SAR data, calibration parameter \( l_{opt} \) can be expressed as follows [35,36]:

\[
l_{opt-HH}(Hrms, \theta, HH) = 0.162 + 3.006(\sin 1.23\theta)^{-1.49}Hrms
\]

\[
l_{opt-HV}(Hrms, \theta, HV) = 0.9157 + 1.2289(\sin 0.1543\theta)^{-0.3139}Hrms
\]

\[
l_{opt-VV}(Hrms, \theta, VV) = 1.281 + 0.134(\sin 0.19\theta)^{-1.59}Hrms
\]

where \( \theta \) is in radians, and \( Hrms \) and \( l_{opt} \) are in centimeters.

The CIEM has been successfully tested in many studies [11,55,56].
3.2. Comparison between CIEM and IEM

Both CIEM and IEM can provide backscattering coefficient values considering the characteristics of the sensor and target. In this section, the difference between IEM and CIEM of SAR for VV and VH polarizations in C-band was studied. In Figure 2, by using IEM, the biases are 4.7 dB in the VV polarization and 0.8 dB in the HV polarization. However, by using CIEM, the biases are 0.8 dB in the VV polarization and −1.8 dB in the HV polarization. In addition, the RMSE between the simulated and measured backscattering coefficient for VV polarization decreased from 5.8 dB to 2.2 dB after using CIEM, and the RMSE for HV polarization decreased from 4.2 to 2.8 dB. The results show that the CIEM performs better than the IEM, as observed by Baghdadi et al. [35,36]. Therefore, only CIEM was used to simulate the backscattering characteristics in this section.

Figure 2. Backscattering coefficients calculated from the integral equation model (IEM) and calibrated integral equation model (CIEM) vs. the observations measured by synthetic aperture radar (SAR) at the C-band: (a) VV polarization, IEM; (b) VH polarization, IEM; (c) VV polarization, CIEM; (d) VH polarization, CIEM.

3.3. Analysis of Simulated Backscattering Coefficient as Functions of Roughness and Soil Moisture

Shi et al. [57] suggested that the backscattering coefficients of a bare soil surface could be presented as a product of two functions on a linear scale:

\[ \sigma_{pq}(\theta) = R_{pq}(\epsilon_s, \theta) \cdot S_{pq}(\theta, kH_{rms}, kl) \]  

(5)

where: 
- \( \sigma_{pq}(\theta) \) is the backscattering coefficient.
- \( R_{pq}(\epsilon_s, \theta) \) is the ground roughness coefficient.
- \( S_{pq}(\theta, kH_{rms}, kl) \) is the soil moisture coefficient.
- \( \epsilon_s \) is the dielectric constant of the soil.
- \( \theta \) is the radar incidence angle.
- \( k \) is the wave number.
- \( H_{rms} \) is the root mean square roughness elevation.
- \( l \) is the correlation length.

This relationship allows for the separation of the contributions of ground roughness and soil moisture to the overall backscattering coefficient.
or on a logarithmic scale \cite{58}:

\[
\sigma_{pq}(\text{dB}) = 10 \log[R_{pq}(\varepsilon_s, \theta) \cdot Sr_{pq}(\theta, kHrms, kl)]
\]  

(6)

One function is the dielectric function \(R_{pq}\) that reflects the soil moisture information; the other is the roughness function \(Sr_{pq}\) that describes the effect of the surface roughness at a different polarization. \(\sigma_{pq}\) is the backscattering coefficient, where subscripts \(q\) and \(p\) represent the polarization status. Meanwhile, \(R_{pq}\) and functions \(Sr_{pq}\) are independent of each other. Firstly, this paper discussed the effects of \(Hrms\) and the empirical correlation length \(lopt\) on the backscattering coefficient using CIEM simulations in this section. Secondly, the effect of soil moisture \(mv\) on the backscattering coefficient using CIEM simulations was analyzed. Finally, the soil moisture inversion model was built using Equation (5) or Equation (6) based on the description of the model, which was built in Sections 3.3.1 and 3.3.2.

3.3.1. Effect of \(Hrms\), Empirical Correlation Length \(lopt\) on the Backscattering Coefficient Using CIEM Simulations

As far as we know \cite{24,40}, two variables describe the surface roughness: \(Hrms\) and correlation length \(l\). Studies have shown that the measurement error of correlation length \(l\) is much larger than that of \(Hrms\) in the contact measurement techniques on roughness because the shorter length profile and large sampling interval in field roughness measurements can result in substantially undervaluing the correlation length \cite{59}. The error between the measured backscattering coefficients and the simulations by CIEM is mainly determined by the inaccuracy of correlation length \(l\) \cite{35}. If the effect of the correlation length on the backscattering coefficient is neglected, it may cause large errors in the estimation of the backscattering coefficient. Therefore, the CIEM in this study did not use the measured correlation length \(l\) but used the empirical correlation length \(lopt\) instead. In building the model, variable incidence angle \(\theta\) and wavelength \(\lambda\) can be considered constant at the C-band. Therefore, the correlation between backscattering coefficient and surface roughness is as follows:

\[
\sigma_{pq}(\theta) = Sr_{pq}(\theta, kHrms, kl_{opt}) = Sr_{pq}(\theta, \frac{2\pi}{\lambda}Hrms, \frac{2\pi}{\lambda}l_{opt}) = Sr_{pq}(Hrms, l_{opt})
\]  

(7)

The calibration correlation length \(lopt\) in VV and HV polarizations can be expressed as Equations (3) and (4) in the CIEM. At the C-band, the incidence angle and frequency are known in VV and HV polarizations of the ENVISAT ASAR data, so variable incidence angle \(\theta\) and frequency \(f\) can be considered constant. Equations (3) and (4) can be expressed as follows:

\[
l_{optpq} = a + bHrms
\]  

(8)

where \(a\) and \(b\) are constants.

Therefore, combining Equations (5) and (7) yields the following expression:

\[
\sigma_{pq}(\theta) = Sr_{pq}(Hrms, l_{opt}) = Sr_{pq}(Hrms, a + bHrms) = Sr_{pq}(Hrms)
\]  

(9)

When the backscattering coefficient was simulated in CIEM, the volumetric soil moisture content was assumed to be 18.6\%, which is the mean of the measured soil moisture at the incidence angle of 33.5°. Incidence angle \(\theta\) is set to 33.5°, and frequency \(f\) is set to 5.405 GHz. The \(Hrms\) was supposed to be 0.5–4 cm using a step size of 0.05 cm, and the corresponding calibration correlation length \(lopt\) was calculated according to Equations (3) and (4). According to Baghdadi et al. (2006), the correlation function in the CIEM is Gaussian \cite{35}. Figure 3 was obtained using statistical analysis.
Figure 3. CIEM simulations of the backscattering signal and $H_{rms}$, empirical correlation length $lopt$ in different fitting relationships (logarithmic and exponential) in VV and VH polarizations: (a) VV, logarithmic; (b) VH, logarithmic; (c) VV, exponential; (d) VH, exponential.

This study found that $R^2$ of the logarithmic relationship in VV and VH polarizations both exceeded 0.98. Therefore, the logarithmic relationship was used to describe the roughness and backscattering coefficient, which can be expressed as follows:

$$\sigma_{pq}(dB) = A \ln(H_{rms}) + B$$

where $A$ and $B$ are the empirical coefficient, which can be calculated by statistical regression analysis.

This result of the study was validated by Baghdadi et al. (2002) [60].

3.3.2. Effect of Soil Moisture $mv$ on the Backscattering Coefficient Using CIEM Simulations

The relationship between soil moisture and backscattering coefficient was analyzed based on a CIEM simulated database under the following conditions: incidence angle $\theta$ is set to 33.5°; frequency $f$ is set to 5.405 GHz; $H_{rms}$ is 1.4 cm; corresponding empirical correlation length $lopt$ can be calculated according to Equations (3) and (4); $mv \in (10\%, 50\%)$ at intervals of 0.5%.

In Figure 4, when the surface roughness and radar configuration are fixed, there are different fitting relationships in VV and VH polarizations using two function expressions (linear and logarithmic). $R^2$ of the logarithmic relationship in VV and VH polarizations is 0.96, and the linear value is 0.85.
The results show that the logarithmic relationship is better between soil moisture and backscattering coefficient, which can be expressed as follows:

\[ \sigma_{pq}(dB) = C \ln(mv) + D \]  \hfill (11)

where \(C\) and \(D\) are the empirical coefficients, which can be calculated by a statistical regression analysis.

![Figure 4. CIEM simulations of the backscattering signal with soil moisture in different fitting relationships (linear and logarithmic) in VV and VH polarizations: (a) VV, linear; (b) VV, logarithmic; (c) VH, linear; (d) VH, logarithmic.](image)

### 3.4. Soil Moisture Retrieval Model

Based on the above analysis, according to Equations (6), (10), and (11), the backscattering coefficient can be expressed as follows at a specific incidence angle and frequency:

\[ \sigma_{pq}(dB) = 10 \log[(A \ln(Hrms) + B)(C \ln(mv) + D)]. \]  \hfill (12)

Therefore,

\[ \sigma_{pq}(dB) = 10 \log[a \ln(mv) + b \ln(Hrms) + c \ln(Hrms) \ln(mv) + d] \]  \hfill (13)

or

\[ a \ln(mv) + b \ln(Hrms) + c \ln(Hrms) \ln(mv) + d = 10(\sigma_{pq}(dB)/10) \]  \hfill (14)

where \(a, b, c,\) and \(d\) are regression coefficients that can be determined by least square methods, and \(p\) and \(q\) are the corresponding polarization mode.
4. Results and discussion

The retrieval model expresses the relationship between $\sigma_{pq}$, $mv$, and $Hrms$ at a specific incidence angle and frequency. When the incidence angle is 25–55°, the logarithmic relationship of Equations (10) and (11) is better. Baghdadi et al. (2006) established that CIEM was calibrated in the C-band for a radar frequency of approximately 5.4 GHz. Therefore, the application condition of Equations (13) and (14) about the frequency is $f = 5.4$ GHz.

Then, the regression coefficients of the inversion model were discussed when the incidence angle changed. The database simulated by CIEM was built under the following conditions: frequency $f$ was 5.4 GHz; $Hrms$ was 0.5–4 cm with a step size of 0.1 cm; $mv \in (10\%, 50\%)$ at intervals of 5%. Furthermore, the incidence angles of the empirical model were 25–55° with an interval of 5° to derive empirical coefficients at different incidence angles. Tables 3 and 4 show the values of empirical parameters $a$, $b$, $c$, and $d$ at different incidence angles. In Tables 3 and 4, when the $Hrms$ was 0.5–4 cm and the incidence angle was 25°, $R^2$ of the empirical coefficient was only 0.57 and 0.79 in VV and VH polarizations, respectively; other values exceeded 0.94. However, Tables 5 and 6 show that when the $Hrms$ was 0.5–2.5 cm, $R^2$ of the empirical coefficient exceeded 0.96 in VV and VH polarizations. Therefore, the simulated values from the empirical model and CIEM compare fairly well at a specific incidence angle in VV and VH polarizations. When the maximum range of $Hrms$ decreased from 4 to 2.5 cm and the soil surface was smooth, the empirical model had high accuracy.

Table 3. Empirical coefficients at different incidence angles in VV polarization ($Hrms \in (0.5, 4)$ cm).

| $\theta$ (°) | $a (\theta)$ | $b (\theta)$ | $c (\theta)$  | $d (\theta)$ | $R^2$ |
|--------------|--------------|--------------|----------------|--------------|-------|
| 25           | 0.0032       | 0.0258       | $-9.592 \times 10^{-5}$ | 0.104     | 0.57  |
| 26.3         | 0.0032       | 0.0286       | $1.973 \times 10^{-4}$  | 0.1007    | 0.72  |
| 30           | 0.0031       | 0.0337       | 0.0008          | 0.0916    | 0.95  |
| 33.5         | 0.0030       | 0.0354       | 0.0011          | 0.0838    | 0.98  |
| 35           | 0.0030       | 0.0355       | 0.0012          | 0.0808    | 0.98  |
| 40           | 0.0029       | 0.0349       | 0.0014          | 0.0720    | 0.98  |
| 45           | 0.0028       | 0.0337       | 0.0015          | 0.0643    | 0.97  |
| 50           | 0.0028       | 0.0317       | 0.0017          | 0.0573    | 0.96  |
| 55           | 0.0029       | 0.0283       | 0.0018          | 0.0505    | 0.94  |

Table 4. Empirical coefficients at different incidence angles in VH polarization ($Hrms \in (0.5, 4)$ cm).

| $\theta$ (°) | $a (\theta)$ | $b (\theta)$ | $c (\theta)$  | $d (\theta)$ | $R^2$ |
|--------------|--------------|--------------|----------------|--------------|-------|
| 25           | 0.0001       | 0.0028       | $2.768 \times 10^{-5}$ | 0.005     | 0.79  |
| 26.3         | 0.0002       | 0.0031       | $4.718 \times 10^{-5}$  | 0.0051    | 0.86  |
| 30           | 0.0002       | 0.0037       | $9.666 \times 10^{-5}$  | 0.005     | 0.97  |
| 33.5         | 0.0002       | 0.0041       | 0.0001          | 0.0053    | 0.99  |
| 35           | 0.0002       | 0.0042       | 0.0001          | 0.0053    | 0.99  |
| 40           | 0.0002       | 0.0045       | 0.0002          | 0.0053    | 0.99  |
| 45           | 0.0002       | 0.0046       | 0.0002          | 0.0051    | 0.99  |
| 50           | 0.0002       | 0.0045       | 0.0002          | 0.0048    | 0.98  |
| 55           | 0.0002       | 0.0041       | 0.0003          | 0.0043    | 0.98  |
Table 5. Empirical coefficients at different incidence angles in VV polarization ($H_{rms} \in (0.5, 2.5)$ cm).

| $\theta$ (°) | $a(\theta)$ | $b(\theta)$ | $c(\theta)$ | $d(\theta)$ | $R^2$ |
|-------------|-------------|-------------|-------------|-------------|------|
| 25          | 0.0037      | 0.0289      | 0.0010      | 0.1018      | 0.97 |
| 30          | 0.0032      | 0.0323      | 0.0011      | 0.0909      | 0.98 |
| 35          | 0.0030      | 0.0320      | 0.0012      | 0.0809      | 0.98 |
| 40          | 0.0029      | 0.0303      | 0.0012      | 0.0723      | 0.98 |
| 45          | 0.0028      | 0.0280      | 0.0012      | 0.0648      | 0.97 |
| 50          | 0.0028      | 0.0252      | 0.0012      | 0.0580      | 0.97 |
| 55          | 0.0029      | 0.0211      | 0.0012      | 0.0541      | 0.96 |

Table 6. Empirical coefficients at different incidence angles in VH polarization ($H_{rms} \in (0.5, 2.5)$ cm).

| $\theta$ (°) | $a(\theta)$ | $b(\theta)$ | $c(\theta)$ | $d(\theta)$ | $R^2$ |
|-------------|-------------|-------------|-------------|-------------|------|
| 25          | 0.0002      | 0.0032      | 0.0001      | 0.0049      | 0.99 |
| 30          | 0.0002      | 0.0036      | 0.0001      | 0.0052      | 0.99 |
| 35          | 0.0002      | 0.0040      | 0.0002      | 0.0053      | 0.99 |
| 40          | 0.0002      | 0.0042      | 0.0002      | 0.0053      | 0.99 |
| 45          | 0.0002      | 0.0042      | 0.0002      | 0.0051      | 0.99 |
| 50          | 0.0002      | 0.0039      | 0.0002      | 0.0049      | 0.99 |
| 55          | 0.0002      | 0.0035      | 0.0002      | 0.0044      | 0.99 |

In summary, the empirical model has good applicability at different incidence angles based on the above analysis. Therefore, the empirical model can be expressed as

$$a(\theta) \ln(mv) + b(\theta) \ln(H_{rms}) + c(\theta) \ln(H_{rms}) \ln(mv) + d(\theta) = 10^{10(s_{pq}(\text{dB})/10)}$$

where $25^\circ \leq \theta \leq 55^\circ$.

5. Model Validation

To evaluate the performance of the retrieval model, the ENVISAT ASAR image was used to retrieve soil moisture in Linze County at an incidence angle of 33.5° and a frequency of 5.4 GHz. From Tables 3 and 4, regression coefficients $a, b, c,$ and $d$ can be obtained as shown in Equations (16) and (17).

$$0.0030 \ln(mv) + 0.0354 \ln(H_{rms}) + 0.0011 \ln(H_{rms}) \ln(mv) + 0.0838 = 10^{10(s_{vv}(\text{dB})/10)}$$

$$0.0002 \ln(mv) + 0.0041 \ln(H_{rms}) + 0.0001 \ln(H_{rms}) \ln(mv) + 0.0053 = 10^{10(s_{vh}(\text{dB})/10)}$$

According to Equation (16), the following formula was obtained:

$$H_{rms} = e^{\frac{10^{s_{vv}(\text{dB})/10} - 0.0838 - 0.0030 \ln(mv)}{0.0030 \ln(mv) + 0.0354 \ln(H_{rms}) + 0.0011 \ln(H_{rms}) \ln(mv) + 0.0838}}$$

By substituting Equation (18) into Equation (17), the soil moisture $mv$ can be calculated by MATLAB. Similarly, the $H_{rms}$ can be calculated. Then, the approach of 3-fold cross validation can be used to validate the model by in situ data. Figures 5 and 6 present the soil moisture and $H_{rms}$ distribution map at the incidence angles of 33.5° and 26.3°, respectively. Figure 5 shows that when the incidence angle was set to 33.5°, the maximum value of soil moisture in the study area was 50%, and the maximum $H_{rms}$ was 4 cm. When the incidence angle was set to 26.3°, the maximum value of soil moisture in the study area was also 50%, and the maximum $H_{rms}$ was also 4 cm. In Figure 5, the brown color indicates higher soil moisture content and $H_{rms}$ and the purple color indicates lower soil moisture content and $H_{rms}$. To evaluate the performance of the retrieval model, the retrieved and measured soil moisture values were compared, as shown in Figure 6. When the incidence angle varied from 33.5° to 26.3°, $R^2$ of the retrieved and measured soil moisture decreased from 0.67 to 0.57, and RMSE increased from 2.53% to 5.4%. In the same situation, when the incidence angle varied from
33.5° to 26.3°, $R^2$ of the retrieved and measured $H_{rms}$ decreased from 0.64 to 0.51, and RMSE increased from 0.33 to 0.4 cm. The results show good consistency between simulated and measured data, but the inversion accuracy of soil moisture is higher than that of surface roughness. When the incidence angle varied from 33.5° to 26.3°, the inversion accuracy of soil moisture and surface roughness decreased. Therefore, it is feasible to invert soil moisture and surface roughness using the empirical model.

Figure 5. Cont.
Figure 5. Distribution map of soil moisture $m_{v}$ and $H_{rms}$: (a) $m_{v}$, $\theta = 33.5^\circ$; (b) $m_{v}$, $\theta = 26.3^\circ$; (c) $H_{rms}$, $\theta = 33.5^\circ$; (d) $H_{rms}$, $\theta = 26.3^\circ$.

Figure 6. Comparison between inverted and ground-measured soil moisture and $H_{rms}$: (a) soil moisture, $\theta = 33.5^\circ$; (b) soil moisture, $\theta = 26.3^\circ$; (c) $H_{rms}$, $\theta = 33.5^\circ$; (d) $H_{rms}$, $\theta = 26.3^\circ$.
6. Conclusions

The paper developed an empirical model to invert both moisture content $\mu$ and surface roughness $H_{rms}$ based on the database simulated by CIEM. In this study, the effects of the surface roughness $H_{rms}$, empirical correlation length $l_{opt}$, and soil moisture $\mu$ on the backscattering coefficient using CIEM simulations were discussed. The relationship of backscattering coefficient $\sigma$, $H_{rms}$ and soil moisture $\mu$ was used to invert the soil moisture and avoid the actual measurement error of correlation length $l$.

The main results of this work are summarized below:

(1) When the incidence angle varied from 33.5° to 26.3°, $R^2$ of the retrieved and measured soil moisture values decreased from 0.67 to 0.57, and RMSE increased from 2.53% to 5.4%. When the incidence angle varied from 33.5° to 26.3°, $R^2$ of the retrieved and measured $H_{rms}$ decreased from 0.64 to 0.51, and RMSE increased from 0.33 to 0.4 cm. The results show that there is good consistency between simulated and measured data, but the inversion accuracy of soil moisture is higher than that of the surface roughness. Thus, using $H_{rms}$ and the empirical correlation length $l_{opt}$ as the roughness parameters in the simulations is sufficient to invert the soil moisture and $H_{rms}$;

(2) The empirical model had favorable validity when the incidence angle was 33.5° and 26.3° at the C-band, but the accuracy was higher when the incidence angle was 33.5°;

(3) It is valid to invert soil moisture and $H_{rms}$ based on CIEM, which uses an empirical correlation length $l_{opt}$ as proposed by Baghdadi, which avoids the actual measurement error of the correlation length and improves the inversion accuracy.

In summary, using $H_{rms}$ and the calibration parameter $l_{opt}$ as the roughness parameters in CIEM is sufficient to invert the soil moisture and soil $H_{rms}$.

However, the computation of incidence angles in CIEM depends on the derivation and verification of the model because of the limited measured data. Therefore, a new incidence angle handling method will be studied. There is a dependence on the research area about the empirical model. In the future, we will attempt to develop a new calibrated advanced integral equation model to optimize the empirical model coefficients, so that the accuracy of soil moisture retrieval can be improved as much as possible.

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