Study of downscaling method for coarse-resolution soil moisture product using combined AirSAR and PALS Radiometer data

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Abstract. As an important component of soil, soil moisture plays an important role in material and energy transmission between hydrosphere, biosphere and atmosphere. It is of great significance to accurately understand the spatial and temporal distribution of soil moisture in large areas. At present, the spaceborne passive microwave remote sensing could achieve the accurate surface soil moisture of large areas, but at the low spatial resolution (10-50km). Therefore, its application was restricted. In this paper, a downscaling algorithm of passive microwave soil moisture products based on C-band backscattering coefficient is developed, and the algorithm is verified by L-band PALS Radiometer data and C-band AirSAR data, the correlation coefficient R between the soil moisture content and the measured value is 0.71, and the root mean square error is 0.053 cm⁻³. According to the verification results of measured data, the downscaling algorithm of soil moisture retrieval products based on C-band backscattering coefficient is reliable.

1. Introduction
As an important component of soil, soil moisture plays an important role in material and energy transmission between hydrosphere, biosphere and atmosphere. It is of great significance to accurately understand the spatial and temporal distribution of soil moisture in large areas for answering many questions in hydrology, meteorology, ecology, soil science and other fields. In recent decades, the rapid development of remote sensing technology provides opportunities for continuous observation of soil moisture in large areas. Soil moisture monitoring based on remote sensing can expand the "point scale" information observed by traditional stations to the "area scale" information more in line with the objective world. In particular, the passive microwave remote sensing is not limited by weather and light conditions, and has the ability to monitor the surface soil moisture all day and all time and a certain penetration ability to vegetation. It is considered to be the most potential means for continuous monitoring of surface soil moisture in large areas. However, the low spatial resolution (10-50km) of passive microwave soil moisture products of spaceborne microwave radiometer has seriously restricted its application in regional drought monitoring and fine management of water resources in irrigation areas. In order to obtain high spatial resolution and high precision passive microwave soil moisture products, lots of scholars have carried out a lot of related research. According to the linear relationship between backscattering coefficient (db form) and soil water content in vegetation area[1-2], and assuming that
the linear relationship between backscattering coefficient and soil water content in low spatial resolution is also suitable for high spatial resolution, Piles (2012) used backscattering coefficient (db form) in high spatial resolution to achieve downscaling of soil water products in low spatial resolution[3]. But the downscaling method proposed by Piles has an obvious disadvantage, that is, it ignores the change of linear coefficient caused by spatial heterogeneity in coarse scale. In this paper, the AIEM model and Tor Vergata model were used to simulate the characteristics of C-band radar backscattering coefficients of different soil moisture in vegetated and non-vegetated areas, and analyze the relationship between soil moisture and backscattering coefficients, and combine the linear relationship between backscattering coefficients and soil moisture in Piles' downscaling method, finally develop a downscaling algorithm of soil moisture products based on C-band backscattering coefficients, The algorithm is verified by C-band AirSAR data and the coarse resolution soil products from L-band PALS radiometer data.

2. Study area and data
In this paper, the data obtained from SMEX02 experiment were used to carry out related research. SMEX02 experiment, a soil moisture monitoring experiment, was carried out in the Walnut Creek Watershed of the United States from middle of June to middle of July 2002. A large number of synchronous observation data of soil moisture, surface temperature, surface roughness and other auxiliary data, such as soil texture, have been obtained [4-6]. Therefore, this paper will use the data obtained from SMEX02 experiment to carry out related research.

The Walnut Creek watershed is located in the Southern small watershed of Ames area, Iowa State, USA, with an average annual precipitation of 835 mm. The main types of vegetation in this area are crops, including corn and soybean, 50% of which are corn crops and 40~45% are soybean crops. At the beginning of the experiment, the corn area were in the initial growth stage, and the soybean area were bare land; by the end of June, the crop biomass in the corn area was 3~4kg/m², and the crop biomass in the soybean area was less than 1kg/m², and the corresponding LAI were about 2 and 0.5, respectively. In addition, in the whole experimental stage, the soil moisture showed multiple dynamic changes[4].

The SMEX02 remote sensing data used in this paper include: C-band airborne synthetic aperture radar (AirSAR) data, L-band airborne passive and active L and S-band sensor (PALS) passive microwave brightness temperature data, vegetation type data and vegetation water content data based on optical data Landsat TM [5-6]. In this paper, the L-band PALS passive microwave brightness temperature data is used for coarse resolution passive microwave soil moisture retrieval. Based on the linear relationship between backscattering coefficient (db form) and incident angle, the incident angle of AIRSAR radar data is normalized to 45° using multi angle data. The specific expression of angle normalization method for linear relationship is as follows [7]:

$$\sigma_{\text{db}}(45°) = \sigma_{\text{db}}(\theta_t) + \gamma \cdot (\theta_t - 45°)$$  

3. Theory and method
In this study, the linear relationship between C-band VV polarization backscattering coefficient (linear form) and soil water content was established to carry out downscaling of soil water products. The linear relationship between VV polarization square backscattering coefficient (linear form) and soil volume water content is as follows:

$$m_v(a, t) = \alpha(a, t) + \beta(a, t) \cdot \sigma_{vv}^0(a, t)$$  

In the above formula, $m_v(\cdot)$ is the volume water content of soil; $\sigma_{vv}^0(a, t)$ is the polarization backscattering coefficient of VV (linear form); $\alpha(\cdot)$ and $\beta(\cdot)$ are the corresponding coefficients; $a$ and $t$ are the pixel scale and the corresponding time, respectively.

According to formula (2), the linear relationship between soil moisture and microwave backscattering coefficient at low spatial resolution (C) is as follows:

$$m_v(C) = \alpha(C) + \beta(C) \cdot \sigma_{vv}^0(C)$$
According to formula (2), the linear relationship between soil moisture and microwave backscattering coefficient at medium and high spatial resolution ($M_j$) is as follows:

$$m_{v}(M_j) = \alpha(M_j) + \beta(M_j) \cdot \sigma_{0v}^2(M_j)$$  \hspace{1cm} (4)

From the formula (3) and (4), the following formula can be obtained:

$$m_{v}(M_j) = m_{v}(C) + \beta(C) \cdot [\sigma_{0v}^2(M_j) - \sigma_{0v}^2(C)] + \left[[\alpha(M_j) - \alpha(C)] + \beta(M_j) - \beta(C) \cdot \sigma_{0v}^2(M_j)\right]$$  \hspace{1cm} (5)

Where the third term represents the heterogeneity term caused by roughness and vegetation parameters in coarse resolution pixels; since the backscattering coefficient of cross polarization is more sensitive to the changes of vegetation morphology and surface roughness parameters, the heterogeneity term in formula (5) can be further simplified as:

$$\left[[\alpha(M_j) - \alpha(C)] + \beta(M_j) - \beta(C) \cdot \sigma_{0v}^2(M_j)\right] = \beta(C) \cdot \Gamma \cdot \left[\sigma_{0v}^2(M_j) - \sigma_{0v}^2(C)\right]$$  \hspace{1cm} (6)

Where $\Gamma$ is the sensitivity factor and $\Gamma = \frac{\partial \sigma_{0v}^2(M_j)}{\partial \sigma_{0v}^2(C)}$.

4. Results

4.1. Simulation analysis of linear relationship

In order to establish the downscaling method, we use the AIEM and Tor Vergata model to simulate the characteristics of C-band radar backscattering coefficients of different soil moisture in vegetated and non-vegetated areas, and analyze the relationship between soil moisture and backscattering coefficients. The parameters of the AIEM model are as follows: The root mean square height $S$ is 0.4cm, 0.8cm and 1.2cm, the surface correlation length $l$ is 4cm, 8cm and 12cm, the surface correlation function is exponential autocorrelation function, the microwave frequency is 5.405GHz (C band), the incidence angle $\theta$ is 40° and the soil volumetric water content $m_{v}$ is 0.05 – 0.40 cm$^3$ · cm$^{-3}$ (interval is 0.01 cm$^3$ · cm$^{-3}$). The relationship between soil VV polarization backscattering coefficient and soil water content is shown in Figure 1-2. The parameters of Tor Vergata model are as follows: the vegetation type is corn, LAI of vegetation is 0.25, 1, 1.75, 2.5, 3.25, 4, 4.75 (corresponding to vegetation water content: 0.28 kg · m$^{-2}$, 1.14 kg · m$^{-2}$, 2.0 kg · m$^{-2}$, 2.94 kg · m$^{-2}$, 3.89 kg · m$^{-2}$, 4.88 kg · m$^{-2}$, 5.9kg · m$^{-2}$ respectively), The root mean square height $S$ is 1.0cm, the surface correlation length $l$ is 8.0cm, the surface correlation function is exponential autocorrelation function, the microwave frequency is 5.33GHz (C-band), the incidence angle $\theta$ is 40° and the soil volumetric water content $m_{v}$ is 0.05 – 0.40 cm$^3$ · cm$^{-3}$ (interval is 0.05 cm$^3$ · cm$^{-3}$). The relationship between VV polarization backscattering coefficient and vegetation water content is shown in Figure 3 and Figure 4.

![Figure 1](image1.png)

**Figure 1.** Relationship between C-band VV polarization backscattering coefficient (db) and soil volume water content in bare soil under different roughness.
Figure 2. Relationship between C-band VV polarization backscattering coefficient (linear) and soil volume water content in bare soil under different roughness.

Figure 1 and Figure 2 show the variation results of soil C-band VV polarization backscattering coefficient in the range of $0.05 - 0.40 \text{ cm}^{-3} \cdot \text{ cm}^{-3}$ of soil moisture under different roughness. It can be seen from the figure that the backscattering coefficient increases with the increase of soil water content. Compared with db backscattering coefficient, linear backscattering coefficient has better linear correlation with soil volume water content, and the linear correlation degree increases with the decrease of roughness.

Figure 3. Relationship between C-band VV polarization backscattering coefficient (db) and soil volumetric water content in vegetation area under different LAI.
Figure 4. Relationship between C-band VV polarization backscattering coefficient (linear) and soil volumetric water content in vegetation area under different LAI.

Figure 3 and Figure 4 show the variation of C-band microwave VV polarization backscattering coefficient with soil water content in the range of $0.05 \leq \text{cm}^{-3} \leq 0.40 \text{cm}^{-3}$ under different LAI. The results show that the linear correlation between db backscattering coefficient and soil water content is poor in low and sparse vegetation area (LAI is small), but with the increase of vegetation LAI (vegetation water content increases), the linear correlation between db backscattering coefficient and soil water content increases, and R tends to 1. In the whole LAI range, the linear backscattering coefficient is highly linear with soil volume water content, R is approximately 1.

4.2. Downscaling of the course resolution soil moisture products of L-band PALS radiometer

Based on the L-band 4000m low spatial resolution passive microwave brightness temperature data of PALS preprocessed on July 5, 7 and 8, 2002, the vertical polarization of single channel algorithm (vertical polarization of single channel algorithm) was used to calculate the soil moisture. Then, according to the downscaling algorithm of soil moisture products based on C-band backscattering coefficient constructed in this paper, the active microwave backscattering coefficient with 800m high spatial resolution in C-band of AirSAR is used to downscale the soil moisture results with 4000m low spatial resolution. Finally, the soil moisture results with 800m high spatial resolution were obtained.
Figure 5. Downscaling results of low spatial resolution L-band passive microwave soil moisture retrieval products.

Figure 6. Comparison of downscaling results of low spatial resolution L-band passive microwave soil moisture retrieval products with site measured values.

The results of low and high spatial resolution of soil moisture (as shown in Figure 5) show that the soil moisture content has an obvious dry wet change process from July 5 to July 7, 2002, that is, the relatively low value of soil moisture content changes from July 5 to July 7 and July 8, which is basically consistent with the actual situation (there is a daily rainfall of 9mm in the study area on July 6). In order to verify the accuracy of soil moisture results with 800m spatial resolution after downscaling, the measured values of soil volume moisture on July 5, July 7 and July 8 were compared with the results with 800m spatial resolution. The analysis results show that (as shown in Figure. 6), the correlation
coefficient $R$ between the soil moisture content and the measured value is 0.71, and the root mean square error (RMSE) is $0.053 \text{ cm}^3 \cdot \text{cm}^{-3}$. Although the RMSE is slightly lower than the validation result of low spatial resolution passive microwave soil moisture accuracy ($RMSE = 0.039 \text{ cm}^3 \cdot \text{cm}^{-3}$) before downscaling, it is still less than $0.06 \text{ cm}^3 \cdot \text{cm}^{-3}$. Therefore, the downscaling research of soil moisture products in this paper has high accuracy.

5. Conclusion

In this paper, considering the variation of linear coefficient caused by spatial heterogeneity in the coarse scale, a downscaling algorithm of soil water products based on C-band backscattering coefficient is established by introducing spatial heterogeneity term. Combined with the L-band passive microwave low spatial resolution soil moisture retrieval results of SMEX02 experiment and the C-band backscatter data of AirSAR, the algorithm is applied to the scale reduction of soil moisture products of PALS passive microwave low spatial resolution. The correlation coefficient $R$ between the soil moisture content and the measured value is 0.71, and the root mean square error is $0.053 \text{ cm}^3 \cdot \text{cm}^{-3}$. According to the verification results of measured data, the downscaling algorithm of soil moisture retrieval products based on C-band backscattering coefficient is reliable.

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