Soil Moisture Retrieval From AMSR-E Data in Xinjiang (China): Models and Validation

Xianfeng Zhang, Jiepeng Zhao, Quan Sun, Xuyang Wang, Yulong Guo, and Jonathan Li

***Abstract*—Accurate soil moisture information is required for studying the global water and energy cycles as well as the carbon cycle. The AMSR-E sensor onboard NASA's Aqua satellite offers a new means to accurately retrieve soil moisture information at a regional and global scale. However, the characterization of the factors such as precipitation, vegetation, cloud, ground roughness, and ice-snow packs is sensitive to the retrieval of the soil moisture content from the remotely sensed data.**

This paper examines the models that are used to generate soil moisture products from US National Snow and Ice Data Center (NSIDC), and to adapt the models to improve the accuracy of soil moisture retrieval in Xinjiang, northwest China. The ground truth data collected by the WET and WatchDog instruments in Xinjiang were used to derive the empirical parameters for the regressive model that are suited to the conditions in Xinjiang. To improve the accuracy of inversion, the impact of precipitation's lag-effect on the surface soil moisture has been addressed using the parameters monthly bases, daily variation and the lag-effect impact of precipitation in the improved model. The improved model is then used to retrieve the soil moisture information from the AMSR-E data. A comparative study between the result from the proposed model and the NSIDC products of May to September 2009 were performed with the AMSR-E data. Validation with ground truth and the comparison indicate that the improved model performs better and produces more accurate soil moisture maps than the NSIDC products in the study area.

***Index Terms*—AMSR-E, arid area, inversion, precipitation, soil moisture.**

I. Introduction

SOIL moisture is a critical environmental element for both global water and energy budgets that have a great impact on climate change over land [1]–[4]. It provides a fundamental condition for vegetation growth and is an important indicator for studying water content in vegetation, monitoring agricultural drought, and predicting crop yield [2], [5]–[7]. Remote sensing has lately been used to deal with large-scale spatial and temporal characterizations of soil moisture fields. Presently three categories of remote sensing methods have been explored, including thermal inertia, remotely sensed vegetation index, or microwave derived coefficients [1], [8]–[11]. Among these methods, the passive microwave remote sensing of soil moisture offers several advantages over the others: (a) ability to penetrate cloud, (b) directly related to soil moisture through the soil dielectric constant, and (c) less sensitive to land surface roughness or vegetation coverage [12], [13].

Within the microwave spectrum, lower frequencies respond to a deeper soil layer and are less attenuated by vegetation. Therefore, they are ideally suited for remote sensing of soil moisture [12]–[15]. The Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) currently acquires passive microwave brightness temperatures at six dual polarized frequencies, centered at 6.9, 10.7, 18.7, 23.8, 36.5, and 89.0 GHz, respectively. The AMSR-E instrument has been onboard NASA's Aqua satellite orbiting the Earth since May 2002. With the exception of regions such as dense vegetation, snow and ice, or frozen soils, AMSR-E provides a global soil moisture coverage every two days, from both the ascending (daytime) and descending (nighttime) overpasses [13]. Existing studies that evaluate near-surface soil moisture fields retrieved from AMSR-E have shown promising results [15], [16]. The models and algorithms designed for soil moisture retrieved from the AMSR-E data can be classified into three types: single-channel-based, multiple-channel-based iterative, and multiple-channel-based regressive algorithms [13], [17], [18]. However, due to the imperfection of the instrument calibration and inversion algorithms and the impacts of precipitation, cloud, ground roughness, ice-snow and dense vegetation covers, the soil moisture products created using a global regressive model in the NSIDC products contain uncertainties in some areas, especially outside the United States [15], [17]. Therefore, much work needs to be done to improve the instrument calibration and inversion algorithms and models, and to address the influential factors more accurately.

This paper demonstrates the utility of passive microwave remote sensing for observing near-surface soil moisture over Xinjiang, a typical arid area in northwest China. The rest of the paper is structured as follows. Section II describes a new empirical inversion model. Section III presents a case study for the AMSR-E derived soil moisture over Xinjiang. A comparative study between the results obtained from the proposed model and that of the NSIDC products from May to September 2009 is discussed in Section IV. Section V draws some conclusions.

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II. Retrieval Methods

A. Retrieval Principles

With the increase of water content in soil, soil dielectric constant also increases rapidly [19]. As a consequence, the emis-

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sivity of passive microwave signals in bands L, S, C, X and Ku decreases considerably with the increase of land surface soil water content [13], [15]. In principle, the microwave signals at frequency of 1.4 GHz can penetrate vegetation cover to detect soil moisture, while a microwave sensor with an operating frequency of 37 GHz can only measure microwave radiation characteristics of vegetation and is unable to detect the soil moisture [20]. Specifically, the AMSR-E sensor has the bands of Ku, X, and C in the low-frequency microwave region and does not have the L band that can penetrate vegetation and surface soil layer. The recently launched ESA's Soil Moisture and Ocean Salinity (SMOS) satellite and upcoming imaging satellites carrying the L-band microwave sensors will allow better soil moisture monitoring in the near future [21], [22].

The models for soil moisture retrieval from AMSR-E data are often built based on the coefficients such as polarization ratios (P_r) calculated from AMSR-E brightness temperature data, which is strongly correlated to vegetation optical depth, surface roughness, and soil water content [17]. The polarization ratio (P_r) is defined as

$$Pr = \frac{(T_{Bv} - T_{Bh})}{(T_{Bv} + T_{Bh})} \tag{1}$$

where T_{Bv} and T_{Bh} are the vertically and horizontally polarized AMSR-E brightness temperatures, respectively.

At a certain incidence angle, Pr decreases quickly with the increase of optical depth [20], [23]. In fact, the related studies indicate that AMSR-E's Pr is correlated with the normalized difference vegetation index (NDVI) derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) data [24], [25]. This indicates that dense vegetation covers have strong impact on the retrieval of underlying soil moisture from the AMSR-E data.

The impact of surface roughness on observed brightness temperature is related to three factors: earth surface characteristics, incidence angle, and frequency [26]. Thus, surface roughness is another critical factor that has impact on AMSR-E Pr, namely that, Pr decreases with greater surface roughness [17]. To remove or reduce the impact of surface roughness on Pr calculation is also quite important for accurate soil moisture retrieval from the AMSR-E data.

B. The Regressive Model for NSIDC Products

According to [17], Pr can be estimated by

$$Pr(sm, g) \approx A(sm)(1 - 2Q)\exp(-\beta\alpha g) \tag{2}$$

$$A(sm) = \frac{(e_{ov} - e_{oh})}{(e_{ov} + e_{oh})} \tag{3}$$

where sm is the soil moisture on a volume basis (%), g is the mixed parameter combining vegetation optical depth (τ_c) with ground surface roughness, $g = h + 2\tau_c$, in which τ_c denotes the vegetation optical depth, h is the proportional to the quantity $(ks)^2$, where k is the wavenumber ($k = 2\pi/\lambda$) and s is the root mean square (RMS) surface height; Q contains the information on both s and the horizontal roughness correlation length l, α and β are the coefficients related to microwave frequency, e_{ov}, and e_{oh} are the vertical and horizontal emissivity of exposed smooth bare land surface, respectively, $A(sm)$ is the function of the product of soil moisture and frequency, and $Pr(sm, g)$ is the function of two independent variables of g and sm.

Due to the fact that g mainly correlates with h and τ_c, it can be treated as a constant in a monthly scale in the same area. If the surface roughness parameter h is ignored, the parameter g is just related to the vegetation condition. If Pr is replaced with the monthly minimum value $Pr_{\min}$, sm becomes correspondingly the monthly lowest value m_v. Thus, by combing (2) and (3), Njoku [17] developed the empirical regressive model shown in (4). This model has been used to create the NSIDC soil moisture products

$$\begin{aligned} sm &= a_3 + b_1 g + b_2(Pr - Pr_{\min})\exp(b_3 g) \\ g &= a_1 + a_2 \ln(Pr_{\min}) \end{aligned} \tag{4}$$

where a and b are the regressive parameters, $Pr_{\min}$ is the monthly minimum base value of Pr calculated from X-band (10.7 GHz) AMSR-E data, sm is the soil moisture on a volume basis. The global base value of $Pr_{\min}$ is calculated from the EASE-GRID of monthly minimum value of soil moisture of the year 2003[17]. Once Pr is calculated from X-band data, the soil moisture can be retrieved using this regression model.

Equation (4) can be further divided into two parts: m_v, reflecting monthly base level of soil moisture, and Δm_v, representing daily or hourly variation of soil moisture. The first part is related to $Pr_{\min}$, and can be empirically expressed as

$$m_v = \mathrm{n}_1 + \mathrm{n}_2 \ln(Pr_{\min}) \tag{5}$$

where n_1 and n_2 are the empirical regression parameters, m_v is the monthly base value of soil moisture, which is impacted by $Pr_{\min}$, and reflects the minimum surface soil moisture level for maintaining the vegetation.

The second part of (4) is related to the $(Pr - Pr_{\min})$ and $Pr_{\min}$, which reflects the variation of surface soil moisture. Thus, the empirical equation of Δm_v can be derived as

$$\Delta m_v = k_1(Pr - Pr_{\min})Pr_{\min}^{k_2} \tag{6}$$

where Δm_v is the daily variation of soil moisture, which is determined by $(Pr - Pr_{\min})$ and $Pr_{\min}$, k_1 and k_2 are best-fit coefficients. The variable Δm_v is caused by land surface evaporation and precipitation, and reflects hourly and daily change of soil moisture and is important to be addressed in the model.

The model shown by (5) depicts the monthly base value of the soil moisture, m_v, which may be inaccurate especially when rainfall occurs for several times and causes larger soil moisture in 5 to 10 cm soil layers. This is commonly termed as "lag-effect". In this case, the monthly base soil moisture value is larger than regular values when less precipitation occurs. The inaccurate estimation of soil moisture also occurs in the case of salty lands and water bodies because these areas are sparsely or non-vegetated but the water content is relatively high. Finally, Njoku's regressive model that is shown in (4) and used in NSIDC is built for a globe scale, and may not be suitable for a specific region such as the arid area of Xinjiang. This is due

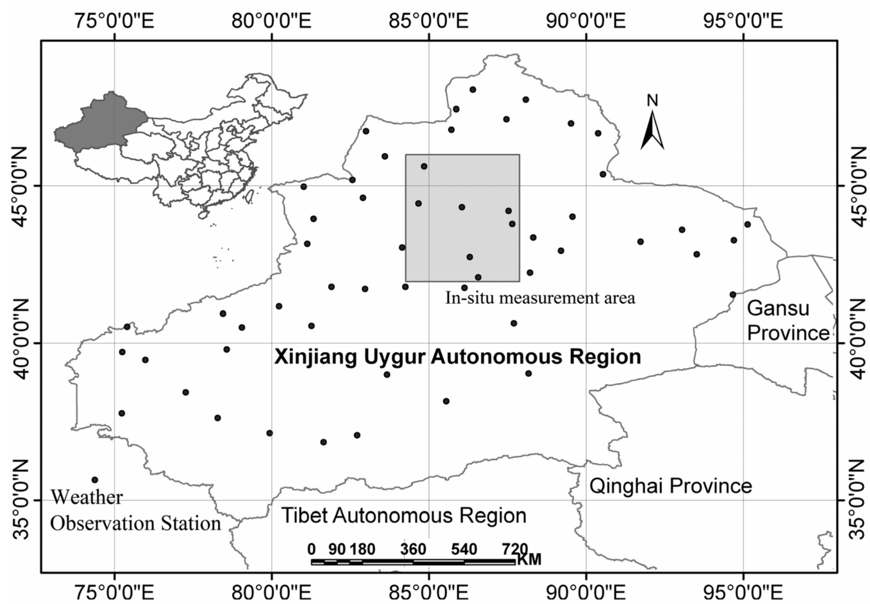

Fig. 1. The location of the study area: Xinjiang, China.

to the limitations of the regressive models themselves. Consequently, some parameters need to be refined or recomputed using specific ground truth data at a regional scale.

C. Adjusted Inversion Model

Based upon the above discussions, improvements will be made to the retrieval model by adjusting the parameters m_v and Δm_v.

In order to remove or reduce the lag-effect impact of precipitation in the study area, a factor m_r is introduced to reflect the impact of precipitation on a monthly base of soil moisture. As (2) indicates, rainfall may lead to the rise of soil moisture, and consequently resulting in a larger value of Pr. At a monthly scale, more precipitation tends to lead to a longer period of high soil moisture, and a higher average value of Pr retrieved from the AMSR-E data. Thus, a variable has been proposed to characterize the lag-effect impact of precipitation in a month.

$$R = \frac{Pr_{\text{mean}} - Pr_{\text{min}}}{c_1 + c_2 Pr_{\text{min}}} \tag{7}$$

where c_1 and c_2 are the empirical parameters, Pr_{mean} is the monthly average of Pr, Pr_{min} is the monthly minimum of Pr. A threshold value of R is empirically estimated as R_0 using the ground truth data of a specific region. If $R > R_0$, the impact of precipitation is strong and the lag-effect impact of precipitation is characterized into the monthly precipitation base m_r by

$$m_r = d(R - R_0) \tag{8}$$

where R_0 and d are the empirical parameters derived from ground truth data. In the case of considering the lag-effect impact of precipitation, the monthly base soil moisture is revised as m'_v, and $m'_v = m_r + m_v$.

The variable Δm_v is generally affected by weather conditions, mainly including precipitation and evaporation, while the impact of precipitation on soil moisture is different in vegetated and non-vegetated areas. In the arid desert area such as Xinjiang, a rainfall process can lead to a larger rise of the surface soil moisture. Empirically, when $Pr > 3Pr_{\text{min}}$, we can assume that a rainfall process is taking place or occurred in a few hours ago. The regression model is suitable for soil moisture retrieval in the case of $Pr_{\text{min}} \leq Pr \leq 3Pr_{\text{min}}$. In contrast, precipitation has a distinct impact on the inversion of the model when Pr is three times bigger than Pr_{min}. In this case, let Pr equals $3Pr_{\text{min}}$, and the Δm_v can be adjusted and better estimated by acknowledging the assumptions above and using (6). The revised regressive model was then used to retrieve soil moisture from the AMSR-E data of Xinjiang, northwest China. Finally, soil moisture can be obtained from the AMSR-E data by

$$sm = m'_v + \Delta m_v = m_v + m_r + \Delta m_v. \tag{9}$$

III. Implementation: A Case Study

A. The Study Area

The study area is located in the northwest of China, including the entire Xinjiang Uygur Autonomous Region (Fig. 1). It is a large, sparsely populated region that covers approximately one sixth of the country's territory. Xinjiang borders the Tibet to the south and Qinghai and Gansu provinces to the southeast, Mongolia to the east, Russia to the north, and Kazakhstan, Kyrgyzstan, Tajikistan, Afghanistan, and the Pakistan- and India-controlled parts of Kashmir to the west. The topography of Xinjiang can be described as "three Mountains delineate two basins": the Mountains Altai, Tianshan, and Kunlun go on the north border, through the center, and on the south border of Xinjiang, respectively. The Zhungeer Basin is bordered by the mountains of Tianshan and Altai, and the Tarim Basin is between the Kunlun and Tianshan Mountains.

The study area is a typical Central Asian arid area with an average annual precipitation of 150 mm, and the spatial distribution of the precipitation is quite heterogeneous. A typical layout

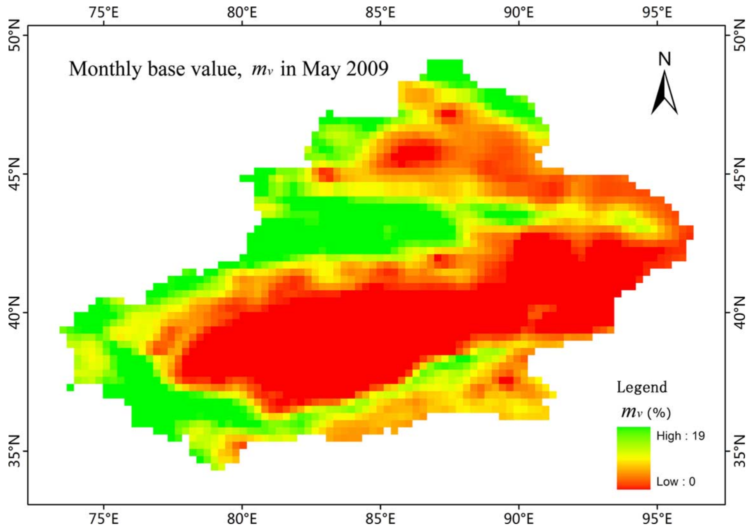

Fig. 2. The base value of soil moisture m_v of May 2009 in Xinjiang.

of landscapes in Xinjiang from the top of a mountain, through the hills, to the central basin is: snow-glacier covers, high-mountain meadows, forest, well-grown high grassland adjacent with the forest, hilly grassland, natural-artificial oasis, and desert. The water resources in Xinjiang are a critical factor for regional eco-environmental and agricultural management and determine the development of the landscapes. Thus, it is significant to monitor soil moisture condition using satellite remotely sensed data.

B. Data Acquisition and Pre-Processing

AMSR-E provides a global soil moisture coverage every two days, from both the ascending (pass through the Equator at daytime 1:30 pm) and descending (at nighttime 1:30 am) overpasses [13]. X-band (10.7 GHz) AMSR-E data are most suitable for soil moisture retrieval due to the fact that the AMSR-E data at frequencies of 36.5 GHz and 18.7 GHz are heavily influenced by clouds while C-band (6.9 GHz) AMSR-E data are subject to radio frequency interference (RFI) [27]. The resampled brightness temperature ($\mathrm{T_B}$) datasets (AMSR-E_L3_DailyLand_V06) of May to September 2009 were used to retrieve soil moisture over Xinjiang. The NSIDC's soil moisture products for the same period were also downloaded for the purpose of conducting a comparative study presented in Section IV.

For the purposes of modeling and validating the proposed regression model, ground truth data have been also collected on the northern slopes of the Tianshan Mountain, a typical area representing Xinjiang's landscapes. Two types of soil moisture data were collected: mobile measurements using the WET instrument developed by the British Company Delta-T Devices, and fixed observations using the WatchDog2400 Irrigation Station, developed by the Spectrum Technologies, Inc., United States. The WET instrument was used to measure the 5–10 cm surface soil moisture of the study area in July, 2008, May and August, 2009, and five WatchDog instruments were set up in the five typical land covers in the study area: forest, meadow, sparse grassland, cotton farmland, and desert, and had continuously collected 5–10 cm hourly soil moisture data from May 7 to October 11, 2009. For calibration purpose, the conventional Loss-on-Drying method was also employed to measure the soil moisture of the known samples, to calibrate the two types of instruments.

C. Implementation

The inversion model proposed in Section II has been implemented using the IDL programming language. A module was developed and integrated along with the pre-processing functions into the ENVI system. The AMSR-E brightness temperature datasets were imported into the ENVI system and pre-processed. The module was used to retrieve the soil moisture of the study area. The comparative study and the validation were also performed in the ENVI system.

D. Retrieval of Soil Moisture in Xinjiang

The *in situ* surface soil moisture dataset and X-band AMSR-E $\mathrm{T_B}$ dataset acquired from May to September, 2009 were used to derive the regressive parameters in (5) and the model of soil moisture retrieval in Xinjiang is

$$m_v = -17.23 - 6.47 \ln\left(Pr_{\min}\right). \tag{10}$$

The monthly base image m_v of Xinjiang for May 2009 was retrieved as shown in Fig. 2 using (10).

As shown in Fig. 2, most areas of Xinjiang are very dry and sparsely vegetated, and some areas are desert (e.g., the Gurbantunggut Desert, and the Taklimakan Desert) with a very low surface soil moisture. The *in situ* measured 5 – 10 cm surface soil moisture on a volume base in the deserts is approximately 1%. The vegetation mainly distributes in the northern and southern slopes of the Tianshan and Kunlun Mountains, and the soil moisture in these areas is much higher than that in the desert areas.

Equation (6) was further used to improve the daily variation of soil moisture Δm_v. The same ground truth and Pr data derived from the AMSR-E T_{B} data were used to estimate the regressive parameters using the methods described in Section II.

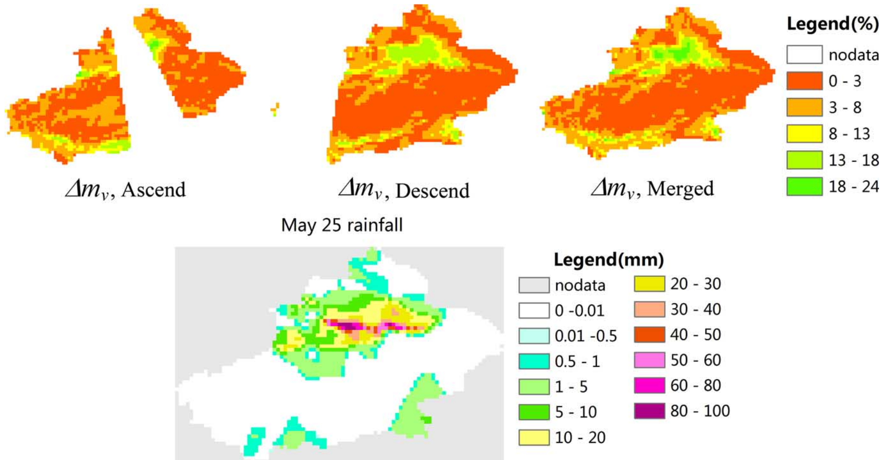

Fig. 3. Comparison between the Δm_v and rainfall data on May 25, 2009.

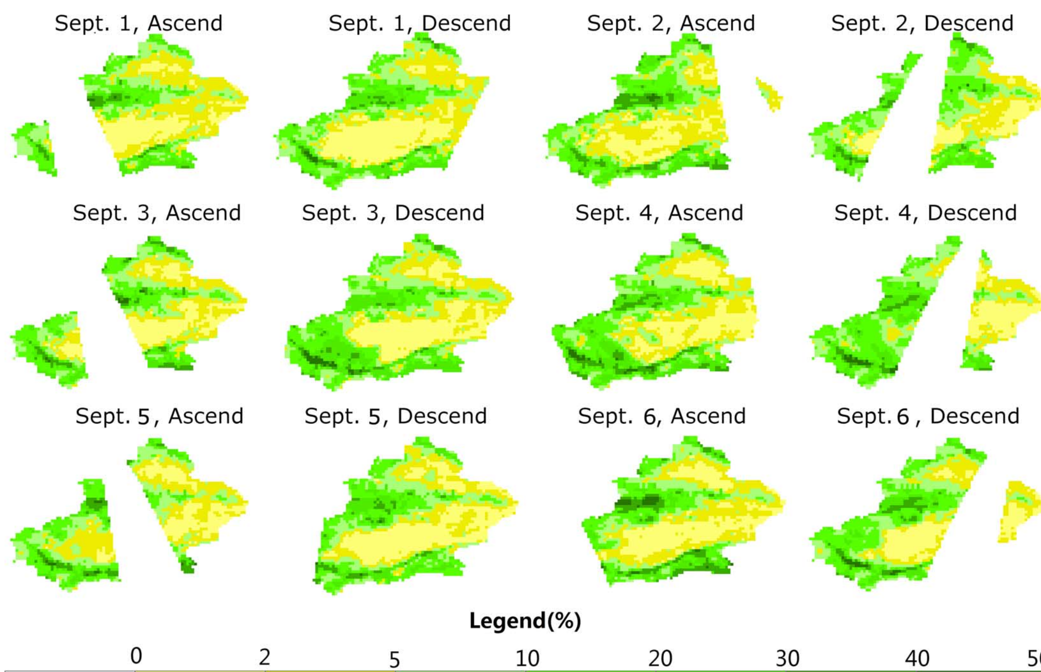

Fig. 4. Soil moisture retrieved from the AMSR-E data of September 1–6, 2009.

When $Pr_{\min} \leq Pr \leq 3Pr_{\min}$, the regressive model was expressed as

$$\Delta m_v = 72.58\,(Pr - Pr_{\min})\,Pr_{\min}^{-0.625}. \tag{11}$$

When $Pr > 3Pr_{\min}$, the regressive model was changed as

$$\Delta m_v = 145.16 Pr_{\min}^{0.365}. \tag{12}$$

The daily variation of soil moisture reflects the impact of precipitation and evaporation. A precipitation process can usually lead to a substantial rise of surface soil moisture very quickly. The factor Δm_v is used exactly for the purpose of characterizing this kind of impact that is not well addressed in the previous empirical models used by the NSIDC products. To elaborate on the effectiveness of this factor, the Δm_v has been further compared with the precipitation data in the same day when AMSR-E data were acquired on May 25, 2009. The precipitation data were extracted from the observation datasets that were collected from the fixed stations (Fig. 1) operated by the China Meteorological Administration (CMA) (Fig. 3).

A quick visual comparison in Fig. 3 indicates that the Δm_v derived from AMSR-E data reflects the impact of rainfall in the northwest area and the southern borders of the study area very well, and the impact on the vegetated areas is relatively weaker than that on the sparsely-vegetated and desert areas. The derived variation of the soil moisture in the center of the rainfall areas is about 18%. Thus, the proposed factor Δm_v is correlated with the precipitation well in Xinjiang.

The parameters for (8) were also regressively derived. The image of m_r can be obtained and used to characterize the lag-effect impact of precipitation and to adjust m_v. Finally, (9) can be

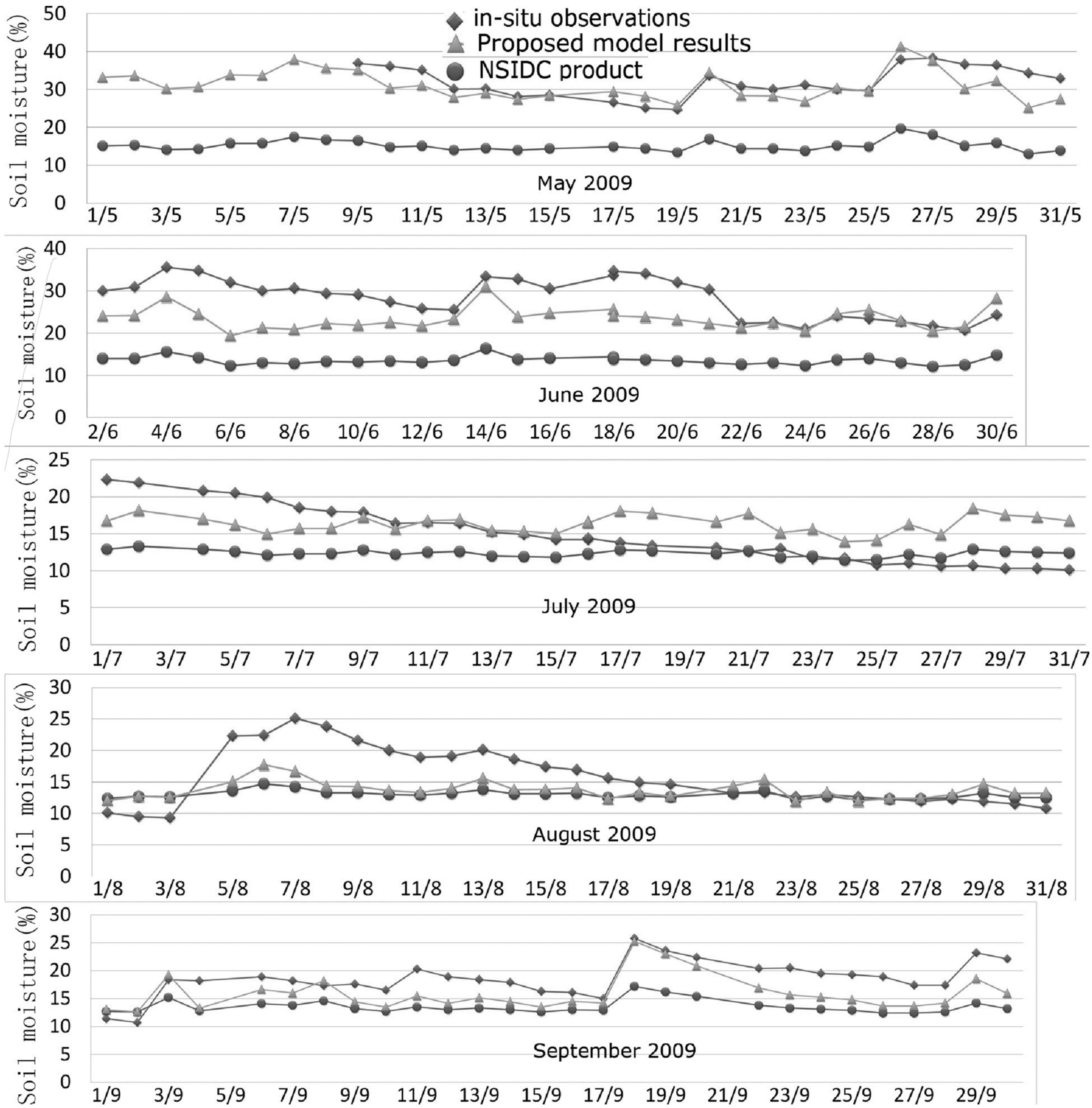

Fig. 5. Comparison of *in situ* measured, NSIDC and the proposed model retrieved soil moisture in the forest cover in May to September, 2009.

used to retrieve the AMSR-E soil moisture over Xinjiang in the period of May to September 2009. Fig. 4 presents the retrieved soil moisture maps of the first six days of September 2009. The result shows that the retrieved soil moisture of the Taklimakan Desert is low in overall (less than 2%), while both sides of the Tianshan and Kunlun Mountains have much higher soil moisture ranging from 10% to 20%. It is interesting to note that the soil moisture of September 2 in the Gurbantunggut Desert is also high. This may indicate that the Desert received a precipitation process. The rainfall records show that a large-scale rainfall occurred in almost the entire north Xinjiang, which well supports our investigation. The same situation is also observed in the Taklimakan Desert, and the precipitation explained the abrupt rise of the soil moisture well in the desert areas. Therefore, the results show that the proposed model performed well in Xinjiang, especially in addressing the impact of rainfall on soil moisture retrieval in the deserts.

IV. Validation and Discussion

A. Assessment of Accuracy

The validation of the AMSR-E retrieved soil moisture information is a difficult task due to the coarse spatial resolution of AMSR-E data with the low frequency channels and the 25×25 km^2 grid resampled from overlapping 45×75 km^2 swath data. It is very difficult to accurately measure the *in situ* surface soil moisture of a 25×25 km^2 grid, where one point measurement or the average of the values at several points is used to represent the soil moisture of the grid. This automatically poses a scale-dependent problem and the *in situ* data may

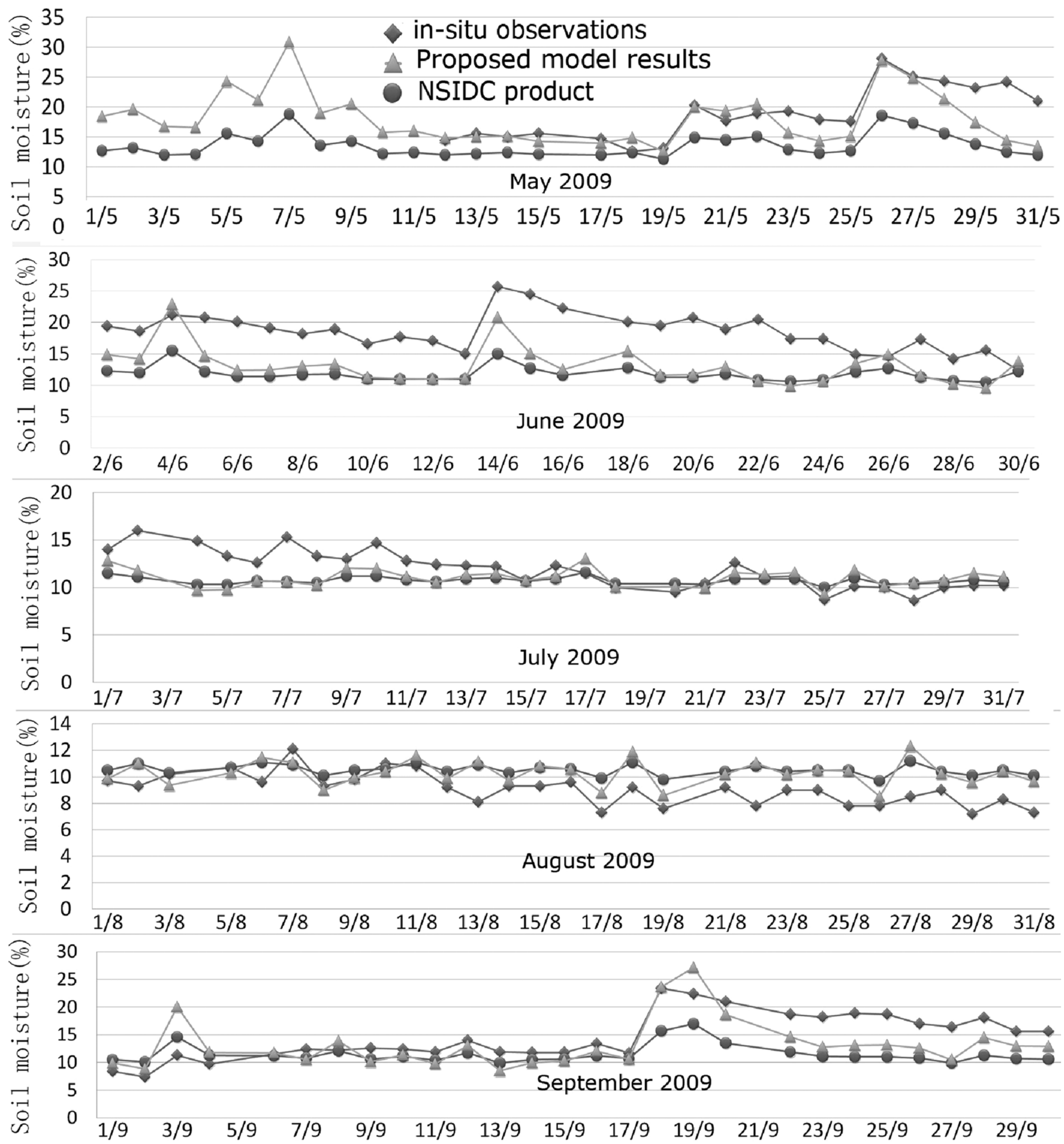

Fig. 6. Comparison of *in situ* measured, NSIDC and the proposed model retrieved soil moisture in the sparse grassland in May to September, 2009.

not be representative of the "real" soil moisture of the grid in the image. On the other hand, the X- and C-band AMSR-E data either has a limited capacity of the surface soil penetration and can only provide 1–2 cm land surface soil moisture estimation [13], [15]. However, the 1–2 cm surface soil moisture changes frequently with rainfall and temperature, and is difficult to measure using *in situ* data. Therefore, in this study the *in situ* data were used to measure the 5–10 cm soil moisture and to represent the "real value" of the surface soil moisture.

As mentioned in Section III, two types of *in situ* soil moisture datasets were collected using the *WET* and WatchDog2400 instruments, respectively. The WET-measured data have a good spatial distribution and the *WatchDog* fixed measurements have a good temporal distribution with an interval of one hour. The WET dataset was first calibrated with the WatchDog dataset using the dataset collected by the traditional Loss-on-Drying method. After that, the WET dataset and half of the WatchDog dataset were used to derive the parameters used in the regressive model. The other half of the WatchDog data were used to validate the model and to conduct the comparative study. The comparison results are illustrated in Figs. 5 and 6, representing land cover types of forest and sparse grassland, respectively.

As shown in Figs. 5 and 6, the soil moisture products downloaded from the NSIDC website are relatively less sensitive to the monthly variation of the soil moisture in the study area, and has larger errors compared to the *in situ* measurements. In comparison to the NSIDC products, the results retrieved using the proposed model have provided better estimation of the surface soil moisture in both forest and sparsely vegetated grassland. In addition, there are systematic differences between the remotely sensed and *in situ* observations of soil moisture. The results obtained by our improved model imply that the AMSR-E surface soil moisture has much fluctuation and reaches back to the original level before precipitation much quicker than the 5 cm *in situ* observations of soil moisture.

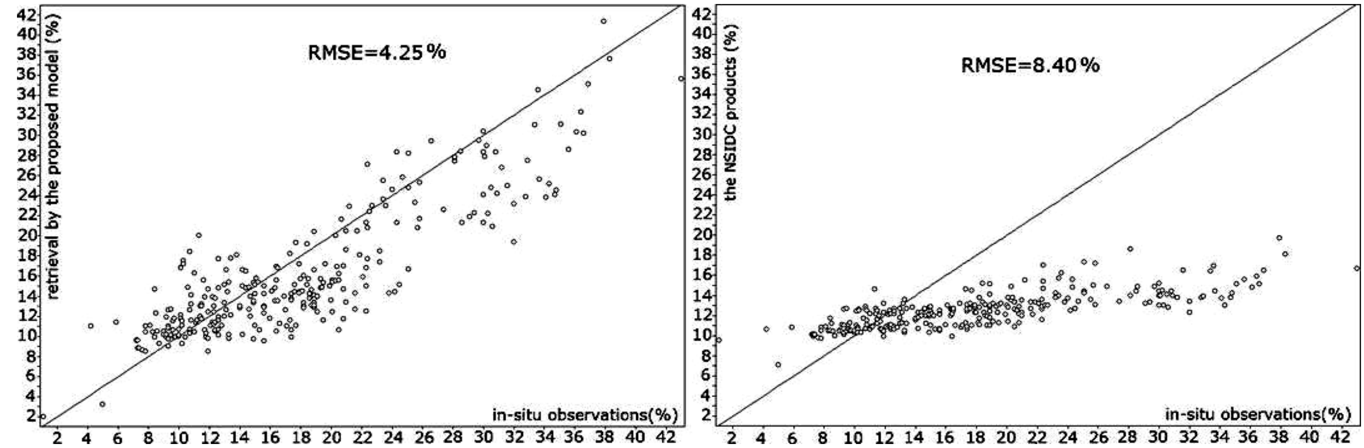

Fig. 7. Correlation of the *in situ* measured soil moisture with the retrievals using the proposed model (left) and with the NSIDC products (right).

TABLE I
STATISTICS OF THE SOIL MOISTURE DATA FROM IN SITU MEASURED AND RETRIEVED FROM THE AMSR-E X-BAND AND THE NCSID PRODUCTS

Samples	Correlation coefficient (R)		RMSE		Mean errors		Maximum errors	
	M1	M2	M1	M2	M1	M2	M1	M2
Sparse-grassland site	0.71	0.71	4.75	3.75	3.7	2.8	11.8	9.8
Forest site	0.70	0.85	10.64	4.59	8.4	3.7	21.5	12.6
Both sites	0.76	0.87	8.40	4.25	6.2	3.3	21.5	12.6

M1: the NCSID products; M2: the proposed model results

The AMSR-E soil moisture data were directly compared to the *in situ* data using the scatter plots as shown in Fig. 7. The horizontal axis represents the point-based *in situ* observation of soil moisture using the WatchDog instrument.

The scatter plots shown in Fig. 7 and the statistics in Table I indicate that the AMSR-E soil moisture retrieved using our improved model has a better correlation with the *in situ* soil moisture obtained using the WatchDog2400 instrument. The AMSR-E soil moisture data have a root mean square error (RMSE) of 4.25%, while the NSIDC product has a RMSE of 8.40%. The mean errors for the NSIDC products and the modified model results are 6.2% and 3.3%, respectively. The maximum errors for them are 21.5% and 12.6%, respectively (Table I). These statistics indicate a considerable improvement in terms of soil moisture retrieval using AMSR-E data over Xinjiang.

B. Comparison of Channels 6.9 GHz and 10.7 GHz

Theoretically, C-band AMSR-E data have a stronger penetration capacity than X-band and was proved the best frequency available in AMSR-E data to estimate soil moisture. However, as mentioned before, the RFI has a strong impact on this frequency and consequently reduces the usability of it in highly populated areas [17]. Can C-band AMSR-E data be more powerful than X-band data for the retrieval of surface soil moisture over Xinjiang? A comparative study was conducted using the same empirical modelling approach in which the parameters were rederived for C-band AMSR-E data from the *in situ* data (Fig. 8).

As shown in Fig. 8, the soil moisture of September 2009 estimated from C-band (6.9 GHz) AMSR-E data are not significantly better than that estimated from X-band (10.7 GHz) AMSR-E data, and appears to be even worse because the RMSE of the C-band AMSR-E soil moisture is 5.35%. This contradiction to the theoretical analysis may be caused by two reasons. First, Xinjiang has a population of more than 21 million and many migrants work for the petroleum and mining industries. The wide spread occurrence of radio frequency interference (RFI) from surface communication networks due to these industries prevents the use of C-band (6.9 GHz) AMSR-E data for soil moisture retrieval. Second, the Pr values calculated from C-band AMSR-E data are not stable and have some abnormal extremum (Fig. 9), which may be caused by the RFI effect [27]. These abnormal extreme values of Pr calculated from C-band AMSR-E data have a negative impact on the proposed empirical model and consequently degrades the capacity of C-band AMSR-E data for soil moisture retrieval. Thus, X-band (10.7 GHz) AMSR-E data were selected in this study for the retrieval of soil moisture over Xinjiang. This comparison shows that the use of the AMSR-E C-band for soil moisture retrieval should be cautious due to the RFI influence caused by strong human activities even in some desert areas such as in Xinjiang.

C. Discussion

Vegetation is a critical factor that impacts the estimation of the soil moisture using passive microwave AMSR-E data. As shown in Fig. 5, the difference between *in situ* and remotely sensed observations of soil moisture in densely vegetated areas (forest) is greater than in sparsely vegetated areas as shown in Fig. 6. This is caused by the fact that X-band AMSR-E data can only penetrate 1–2 cm into the surface soil. Our proposed inversion model is a semi-empirical model based on the 5 cm *in situ* surface soil moisture data, which is more suitable than 1–2 cm data for most applications such as environmental and agricultural management. L-band microwave SMOS satellite launched recently by the European Space Agency (ESA) provides a new opportunity to achieve a better estimation of soil moisture in densely

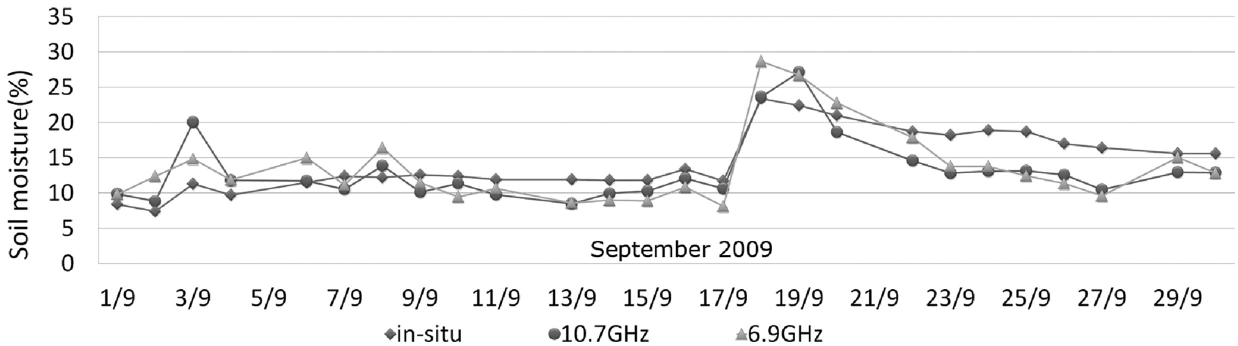

Fig. 8. Comparison of *in situ* measured, 6.9 GHz and 10.7 GHz retrieved soil moisture in the sparse grassland in September 2009.

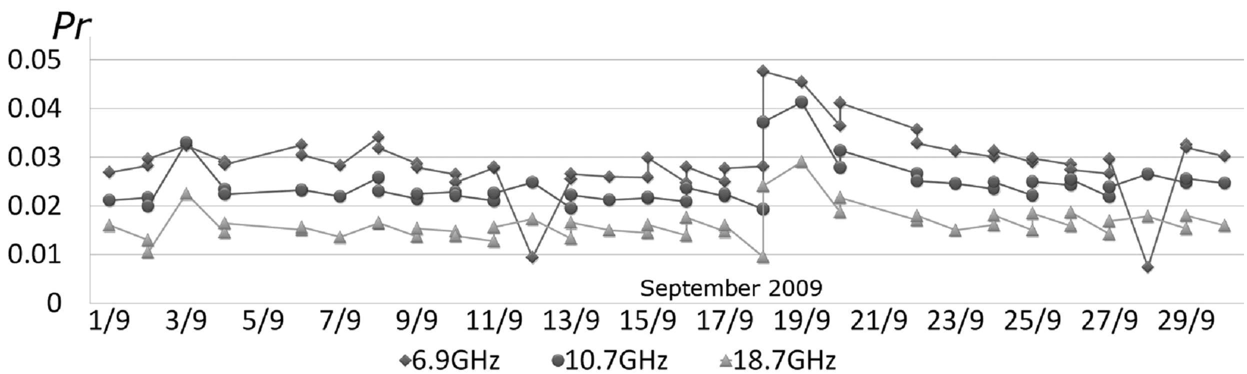

Fig. 9. The scattering plot of the Pr values of September 2009 calculated from the 6.9 GHz, 10.7 GHz and 18.7 GHz channels.

vegetated areas. Nevertheless, a reliable result was achieved from X-band AMSR-E brightness temperature data using our model (Fig. 7) in the moderately and sparsely vegetated regions in Xinjiang.

Although the impact of precipitation on AMSR-E soil moisture was addressed in the proposed model, the feedbacks of the surface soil moisture in the depths of 1–2 cm and 5–10 cm are different to the precipitation. The 1 cm soil moisture changes fast and responds quickly to a rainfall process. When the rainfall stops, the surface soil layer also dries fast, but the 5–10 cm soil layers tend to keep a higher water content in a short period of time. Thus, the vertical variation and different response to a rainfall process also leads to the difficulty of soil moisture retrieval and validation when the *in situ* measurements are used as "real values" to validate the model-based estimates. In this case, the remote sensing based estimation values of soil moisture are lower than those of the *in situ* measurement. Furthermore, the ground measuring instrument (e.g., WET and WatchDog) used in this study also has errors when used to measure the soil moisture of a type of soil in field.

Although the empirical model is built based on AMSR-E data and *in situ* observation of soil moisture, the relationship between the surface soil moisture and the remotely sensed derivatives should keep consistent to some extent if the landscape and climate are same or similar to the study area. Thus, this empirical model can be used directly in the similar areas such as Africa or Arizona deserts. The inaccuracy of the estimation of soil moisture mainly lies in the different land use patterns and larger errors may occur in the agricultural areas due to the diverse irrigation and cultivation patterns. It is recommended that further verification of the parameters for the proposed model should be performed when it is transplanted from one area to another similar area and larger errors may be resulted when no *in situ* measurement is available.

V. Conclusions

This study has demonstrated that useful soil moisture information over Xinjiang can be retrieved from passive microwave remotely sensed data from the AMSR-E instrument. The proposed regressive model works well in addressing the impact of precipitation on soil moisture by adding the lag-effect factor m_r, and dividing the soil moisture into monthly base value m_v and daily variation Δm_v, and localizing the regressive parameters using the *in situ* measurement of the study area. The validation indicates that the proposed model is more effective in retrieval of soil moisture from AMSR-E data over Xinjiang. Furthermore, the soil moisture products from NSIDC vary within a relatively narrower range of values from approximately 10% to 18%, while the soil moisture in arid and desert areas usually have a wide range of soil moisture variation. Specifically in the study area, the soil moisture in the Tianshan Mountain area is much higher than that in the desert areas. In this case, the NSIDC products have a lower estimation of soil moisture for the Tianshan Mountain area, and a higher estimation for the desert areas. The results from the improved model in this study have shown a better estimation in both the vegetated mountain areas and sparsely or non-vegetated desert areas, with a value of up to 40% and below 2%, respectively. Thus, the improved model has a better performance in the inversion of soil moisture from AMSR-E data with a RMSE of 4.24%, which is nearly half of the RMSE value associated with the NSIDC products. The comparison between X- and C-band AMSR-E data indicates that the former performed better than the latter in terms of retrieval of soil moisture over Xinjiang.

Due to the coarser spatial resolution and the lack of detailed characterization of land covers, further improvement in soil moisture retrieval from AMSR-E data needs to incorporate radar, visible/near-infrared data, and the data assimilation strategy to co-inverse the soil moisture [28]–[32]. In addition, use of L-band microwave data available from the recently launched SMOS satellite may improve performance of remotely sensed soil moisture. It is believed that soil moisture can be better estimated from remotely sensed data in the near future.

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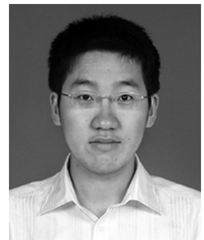

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