

Retrieving High-Resolution Surface Soil Moisture by Downscaling AMSR-E Brightness Temperature Using MODIS LST and NDVI Data

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Abstract—A method to retrieve soil moisture at high spatial resolution is presented in this paper. The method is based on soil moisture retrieval with passive brightness temperature. The method of retrieving land surface temperature with passive microwave is combined with the relationship between the microwave polarization difference index (MPDI) and normalized difference of vegetation index (NDVI) to obtain high-resolution microwave brightness temperature and soil moisture. Advanced Microwave Scanning Radiometer—Earth Observing System (AMSR-E) 18.7-GHz brightness temperature at 25-km resolution is downscaled to 1-km using high-resolution MODIS visible/infrared (VIS/IR) data. High-resolution soil moisture is retrieved with the downscaled microwave brightness temperature using a single-channel algorithm (SCA) and the Qp model to deal with the influence of roughness. The method is applied to an area in northwest of China. The downscaled high-resolution soil moisture is tested with ground data collected at three sites within the Maqu monitoring network from July 1, 2008 to June 30, 2009. The trend of the time series of the downscaled soil moisture is similar to the ground measurements during this period with root mean-square error (RMSE) less than 0.12. The results show that the method is more suitable to moderate to drier soil conditions with bare surface or covered by sparse vegetation.

Index Terms—Downscaling, high resolution, microwave brightness temperature, soil moisture.

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I. INTRODUCTION

SOIL moisture is a key variable in the water and energy exchanges that occur at the land-surface/atmosphere interface. Observations contribute significantly towards the improvement of weather and climate forecast and understanding terrestrial ecosystem processes [1]–[3]. Both microwave and optical/thermal infrared remote sensing techniques have been used to estimate soil moisture [4], [5]. Passive microwave remote sensing is the most promising technique for global monitoring of soil moisture due to the direct relationship between soil emissivity and soil water content [6]. It also has the advantage of all-weather observations and penetration into the vegetation canopy. There are many microwave radiometers used for soil moisture observation, such as special sensor microwave/imager (SSM/I), AMSR-E, soil moisture and ocean salinity (SMOS). Soil moisture products have been generated using either AMSR-E or SMOS data and assessed in many studies [7], [8]. However, the spatial resolution of passive microwave sensors is often poor, most of which is lower than 25 km. Soil moisture retrieved by passive microwave observations is usually not sufficient for regional scale studies due to its coarse spatial resolution, soil moisture data at higher resolution is needed [9], [10].

Many studies concentrate on downscaling soil moisture with high resolution optical/thermal and radar data [10]–[12]. Methods of “universal triangle” [10] utilizing the feature spaced of remotely sensed land surface radiative temperature over heterogeneous areas against vegetation index (VI) have been proven to be a feasible way to derive high resolution soil moisture. Such a method needs a wide range of both NDVI and surface moisture conditions within the study region. Physical and theoretical methods to disaggregate soil moisture from SMOS data also use optical/thermal data [11]. The principle of soil moisture observation with radar is the same as with passive microwave; many studies use Radar data to downscale soil moisture from passive microwave observations [12]. However, the applicability of these algorithms is restricted by the requirement of large volume of high-resolution data that are not available at global scale with high observation frequency.

This paper proposes a different method to retrieve high-resolution soil moisture from high-resolution brightness temperature using the single-channel algorithm (SCA) [13] and the Qp model [14], [15] to deal with the influence of soil roughness. High-resolution brightness temperature can be retrieved by downscaling passive microwave brightness temperature using

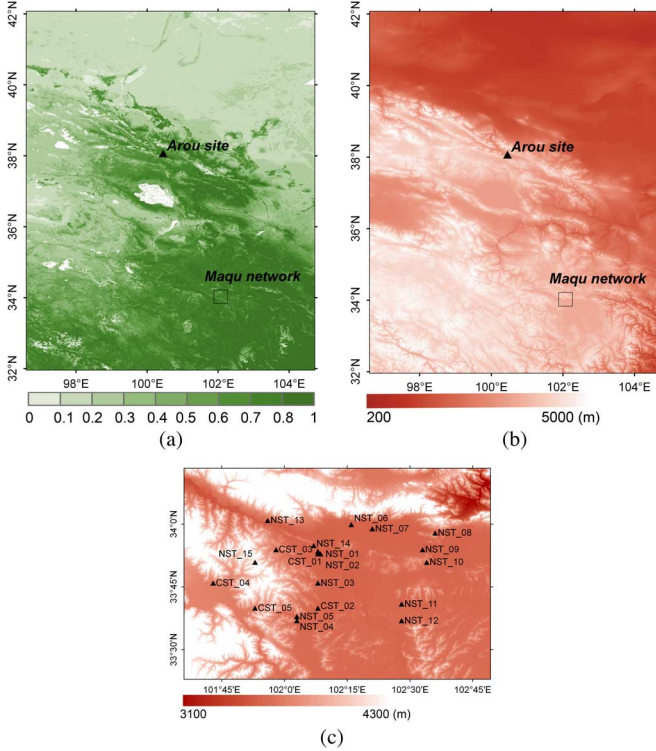


Fig. 1. (a) NDVI of the study area and (b) STRM DEM of the study area and (c) Maqu monitoring network on July 6, 2008.

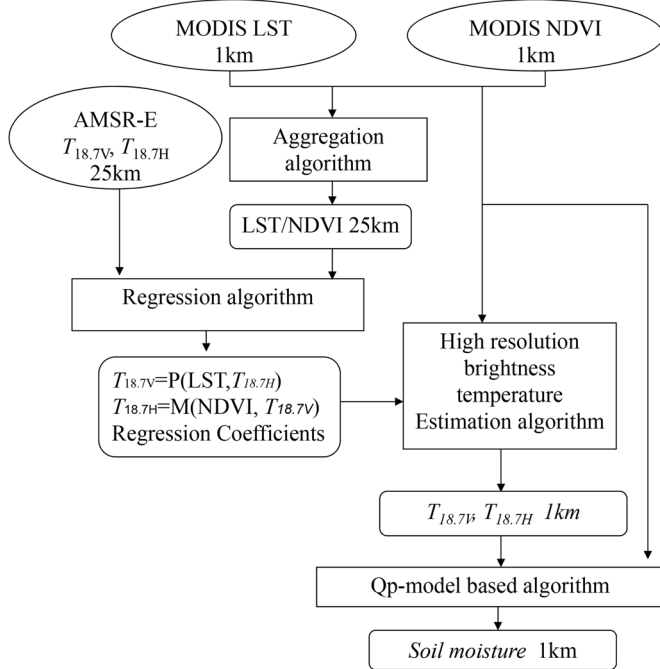


Fig. 2. Schematic flow diagram for high-resolution soil moisture estimation algorithm.

high resolution land surface temperature (LST) and NDVI data. The algorithm of downscaling brightness temperature is based on the method of retrieving the LST from passive microwave observation [16] and the relationship between microwave polarization difference index (MPDI) and NDVI [17]–[19].

II. DATA AND STUDY AREA

The study area is in the northwest of China and located between 97° and 105°E and 32°10' – 42°N. Fig. 1(a) and (b) shows the spatial distribution of NDVI and shuttle radar topography mission digital elevation model data (STRM DEM) [20] of the study area on July 6, 2008. The north of the area is the Heihe River Basin, which is characterized by very different land covers over the entire basin from glacier, frozen soil, alpine meadow and forest in the upper reach, irrigated crops in the middle reach, riparian ecosystem, and desert in the down streams. The south of the area covers the large valley of the river and the surrounding hills, characterized by a uniform land cover of short grassland and forest, especially in the southeast part where Maqu soil moisture network stations are located.

The AMSR-E level 3 product of the 18.7-GHz band double-polarization brightness temperature, MODIS MYD11A1 1 km daily land surface temperature and MOD13A2 16-day NDVI are downloaded from the National Snow and Ice Data Center (NSIDC).

In situ soil moisture data were collected from the Maqu network [21] in a cold humid environment and **Arou freeze/thaw observation site** [22] during July 1, 2008 to June 30, 2010. The satellite data are also from this period.

The Maqu network is located at the northeastern edge of the Tibetan Plateau and consists of 20 sites (or nodes) [Fig. 1(c)]. Soil moisture and soil temperature at different depths (from 5 cm to 80 cm below surface) are measured at 15-min intervals. Two sites located in a relatively flat area are selected to test the retrieved soil moisture. One is the CST01, located in the river valley, and the nearest mountain is 1.5 km far away. The land cover type of the area surrounding the CST01 site is grass, and the elevation is about 3430 m. The other site is NST09, also located in the river valley, and the surrounding of the site is relatively flat. The ground measurements of soil moisture at 5 cm depth with 1-h interval from sites CST01 and NST09 are used to test the results of the retrieved high-resolution soil moisture.

The Arou freeze/thaw observation is one of the experimental sites of the Watershed Allied Telemetry Experimental Research (WATER) project [22] and located in the middle reach of the Babao River Basin (upper stream of Heihe River); the nearest mountain is located about 3 km away. Soil moisture at depths of 10 to 160 cm was measured at 30-min intervals at the Arou site and used in this study.

III. METHOD

The method is based on the soil moisture retrieval algorithm with brightness temperature observed in microwave bands. The 25-km microwave radiometric brightness temperatures are downscaled with the 1-km MODIS LST and NDVI data to retrieve 1-km soil moisture. The flowchart of the method is given in Fig. 2, and details are described in the following sections.

A. Soil Moisture Retrieval With Brightness Temperature

The single-channel algorithm (SCA) is a robust algorithm that is based on the zero-order radiative transfer model ($\tau - \omega$ model) [23]. Brightness temperature from the space-borne radiometer can be formulated by radiative transfer model ($\tau -$

ω model), which just contains two layers of soil and vegetation canopy. Soil surface emissivity can be obtained by correcting brightness temperature with surface temperature, vegetation water content, which can be estimated with NDVI [24].

The Qp model is used to minimize the effects of surface roughness on estimating the soil dielectric constant from soil surface emissivity. The Qp model relates the two polarization rough surface emissivity to the dual-polarization Fresnel transmissivity, without the need of a roughness parameter [14]. At last, dielectric constant and soil texture data are input to the Dobson model [25] to get the soil moisture.

Soil moisture can be written as a function of dual-polarization microwave brightness temperature, land surface temperature, and NDVI and can be written as

$$SM = G(T_{18.7V}, T_{18.7H}, T_S, NDVI) \quad (1)$$

where SM is soil moisture, $T_{18.7V}$ and $T_{18.7H}$ are V- and H-polarization brightness temperature at 18.7 GHz, and T_S is land surface temperature.

As LST and NDVI can be obtained at high resolution, once $T_{18.7V}$ and $T_{18.7H}$ are known at high resolution, soil moisture can be retrieved at the same resolution

B. Downscaling Brightness Temperature

In order to retrieve high-resolution soil moisture, brightness temperature at 25 km should be downscaled to high resolution. The method of downscaling brightness temperature is based on the method of retrieving land surface temperature from passive microwave observation [16] and the relationship between MPDI and NDVI [17]–[19].

The algorithm [16] of retrieving land surface temperature uses 36.5 GHz V polarization brightness temperature as the primary channel, and the difference between the 36.5-GHz V- and 18.7-GHz H-polarization brightness temperature are used to eliminate the influence of soil water. In order to simplify the algorithm, only the influence of soil water is considered, and 18.7-GHz V-polarization can be used to replace 36.5-GHz V-polarization as the primary channel to retrieve the land surface temperature. This is because both Ku (18.7 GHz) and Ka (36.5 GHz) band V-polarization are suitable for retrieving land surface temperature [26]. The equation of retrieving LST from microwave brightness temperature can be written as

$$T_s = C_0 + C_1 * T_{18.7V} + C_2 * (T_{18.7V} - T_{18.7H}) \quad (2)$$

where C_0 , C_1 , and C_2 are coefficients. Equation (2) can be rewritten as

$$T_{18.7V} = D_0 + D_1 * T_s + D_2 * T_{18.7H} \quad (3)$$

where D_0 , D_1 , D_2 are coefficients.

Assuming that the influence of atmosphere on 18.7 GHz V- and H-polarization is the same, (3) can minimize the influence of atmosphere.

Even if other variables in (3) are known, $T_{18.7V}$ and $T_{18.7H}$ cannot be obtained simultaneously using only one equation. An additional equation is needed to estimate $T_{18.7V}$ and $T_{18.7H}$.

MPDI can be written as (4) for 18.7 GHz frequency

$$MPDI = (T_{18.7V} - T_{18.7H}) / (T_{18.7V} + T_{18.7H}). \quad (4)$$

Studies have found the exponential relationship between MPDI and NDVI [17], as follows:

$$NDVI = E_0 + E_1 * \exp(E_2 * MPDI) \quad (5)$$

where E_0 , E_1 , and E_2 are coefficients.

Combining (4) and (5), we obtain

$$T_{18.7H} = \frac{1 - F_1 * \ln(F_2 * (NDVI - F_0))}{1 + F_1 * \ln(F_2 * (NDVI - F_0))} * T_{18.7V} \quad (6)$$

where F_0 , F_1 , and F_2 are coefficients.

Once the coefficients of (3) and (6) are known, $T_{18.7V}$ and $T_{18.7H}$ can be calculated by resolving the equation series. We assume that (3) and (6) are scale independent for the same region, they can be applied to high-resolution LST/NDVI data to estimate brightness temperature at high resolution.

C. High Resolution Soil Moisture Retrieval Method

The approach for high-resolution soil moisture retrieval involves three steps:

First, LST and NDVI, available at high resolution, are aggregated to the microwave resolution for the purpose of obtaining the regression coefficients in (3) and (6) with AMSR-E 18.7-GHz dual-polarization brightness temperatures.

Second, these equations, in conjunction with high-resolution NDVI and LST, are then used to obtain brightness temperature at high resolution.

Third, high-resolution brightness temperature is used to retrieve high-resolution soil moisture with high-resolution MODIS LST/NDVI data using SCA and Qp model.

IV. RESULT AND DISCUSSION

A. Relationship Between Microwave Brightness Temperature and LST/NDVI

Equations (3) and (6) are applied to the study area from July 1, 2008 to June 30, 2009, the determinant coefficient R^2 is shown in Fig. 3.

Fig. 3(a) shows the R^2 of the relationship between the microwave brightness temperature and MODIS LST as described by (3) over the study area. Data are selected according to two thresholds: 1) cloudy pixels in MODIS LST are excluded and 2) only pixels where LST are larger than 275 K are used. Under such thresholds, AMSR-E ascending data in most days of the year and descending data of summer months are used. The R^2 of (3) is higher than 0.5 in most days of the year using ascending and descending data in Fig. 3(a).

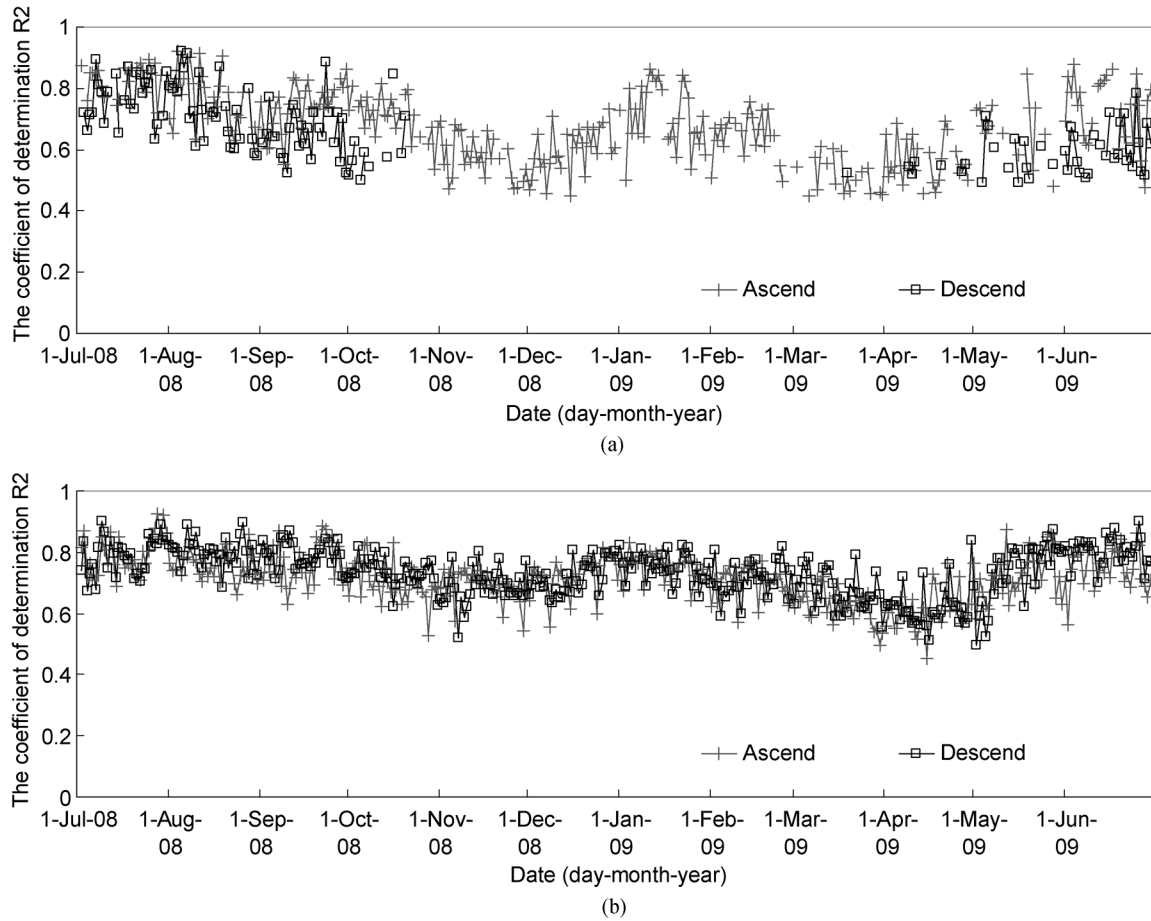


Fig. 3. Coefficient of determination R^2 (a) for (3) and (b) for (6) from July 1, 2008 to June 30, 2009 in the study area.

Fig. 3(b) shows the R^2 of (6). The values of R^2 are higher than 0.6 in most days of the year for both ascending and descending data, especially from July to September in 2008 and June in 2009 when R^2 is higher than 0.7. From October 2008 to May 2009, the relationship is less stable with R^2 lower than 0.6 (but still higher than 0.5) for some days. This is because this period is in the nongrowing season, the average and standard deviation of NDVI in the study area is small, and the range of NDVI value is limited.

It is found the values of R^2 of (3) and (6) is quite close on day and night periods (under the condition of LST larger than 275 K); this implies that the relationships described by the two equations are applicable to both day and night time.

Two subsets of data are selected to evaluate the influence of the vegetation density on (6): one is from the south of the study area covered by grass and forest with NDVI higher than 0.5; the other one is from the middle of study area covered by grass with NDVI lower than 0.5 but higher than 0.1. The two subsets are applied to (6). Fig. 4 shows the R^2 of (6) from July to September 2008 of the two subsets. It is found that the R^2 values are higher in the middle of the study area than those in the south. This is because (6) is based on the power relationship between MPDI and NDVI, a wider range of value of NDVI is needed to build the power relationship.

To ensure higher accuracy in applying (3) and (6), the optimum conditions are as follows: 1) LST is larger than 275 K and 2) the range of NDVI is between 0.1 and 0.5.

B. Evaluation of the Method of Downscaling Brightness Temperature

To evaluate the performance of the method of downscaling microwave brightness temperature, a three-step algorithm is proposed: firstly the 25-km AMSR-E brightness temperature is upscaled to 75-km by averaging 3×3 pixels of 25-km AMSR-E brightness temperature; second, the upscaled 75-km AMSR-E brightness temperature is re-downscaled to 25-km using the brightness temperature downscaling method described in Section III; third, the downscaled brightness temperature from 75-km to 25-km is compared with the original 25-km AMSR-E brightness temperature.

The results on July 18, 2008 and June 26, 2009 in the study area are shown in Fig. 5. The comparison between the two 25-km brightness temperature gives R^2 higher than 0.6 and RMSE less than 7 K. It is found that the results from V-polarization is better (RMSE smaller than 5 K and R^2 larger than 0.7) than that from H-polarization.

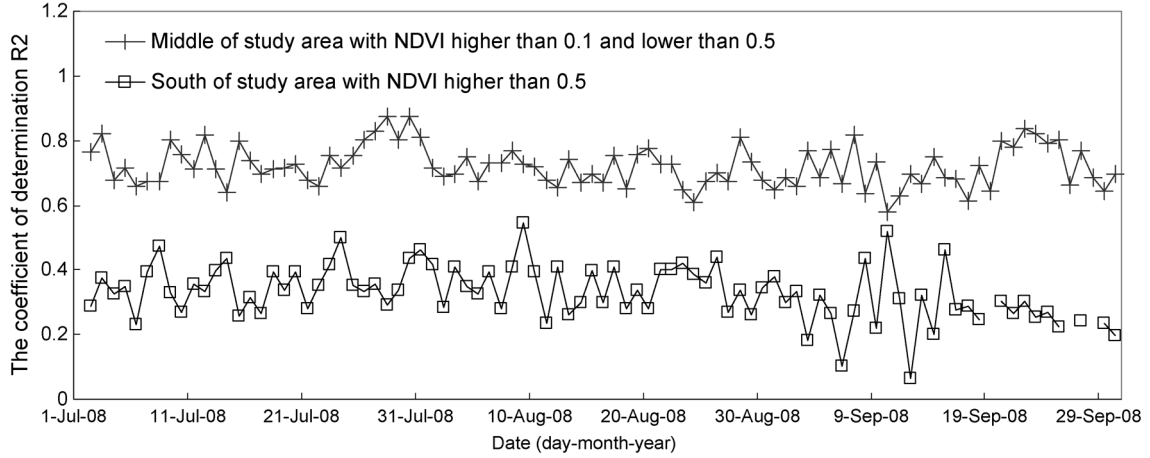


Fig. 4. Coefficient of determination R^2 for (6) with different vegetation cover from July 1, 2008 to June 30, 2009.

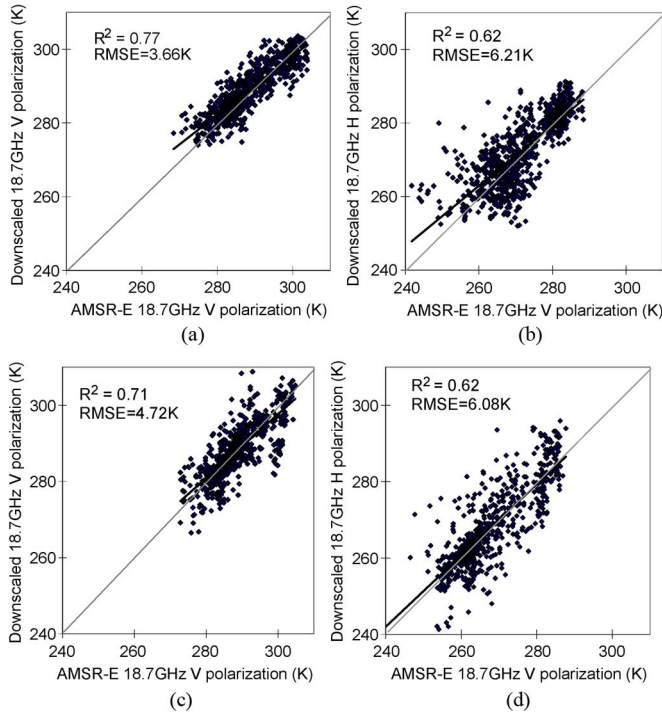


Fig. 5. Scatter plots of downscaled 18.7-GHz brightness temperature and original AMSR-E 18.7-GHz brightness temperature. (a) and (b): 18.7-GHz V- and H-polarization brightness temperature on July 18, 2008; (c) and (d): 18.7-GHz V- and H-polarization brightness temperature on June 26, 2009.

C. High Resolution Soil Moisture

Soil moisture is then retrieved by applying the improved SCA SCA algorithm using the Qp model to the downscaled high-resolution brightness temperature at 1 km.

Fig. 6 shows an example of the retrieved soil moisture at 1 km on July 23, 2008. To evaluate the spatial distribution of the downscaled soil moisture, the 25-km soil moisture product jointly produced by Vrije University Amsterdam (VUA) and NASA (<http://geoservices.falw.vu.nl/>), which is obtained from AMSR-E data using the Land Parameter Retrieval Model (LPRM) retrieval model [27], is also shown in Fig. 6. Due to cloud effect on MODIS LST data, the effective area of

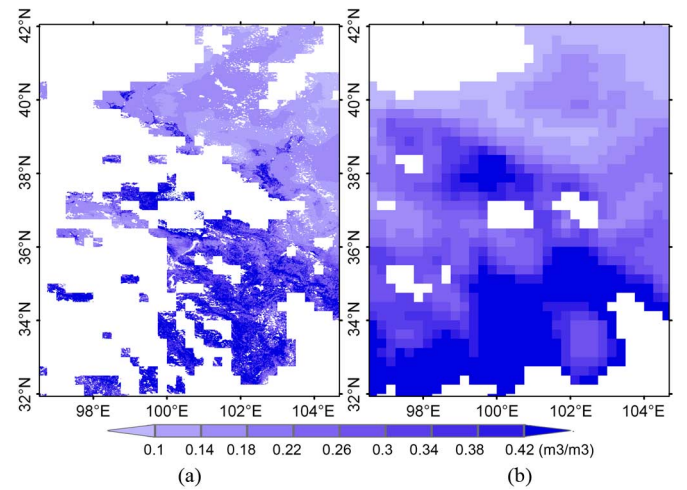


Fig. 6. (a) Retrieved soil moisture at 1 km and (b) AMSR-E soil moisture product at 25 km on July 23, 2008.

the retrieved soil moisture at 1 km is less than those in the VUA-NASA soil moisture product [see white area in Fig. 6(a)]. The spatial pattern of the two maps of soil moisture in Fig. 6 is correlated to each other over the study area, and soil is wetter in the southern area than in the northern area of the study region.

The retrieved 1-km soil moisture is evaluated by comparison with the ground measurements. Ideally, more points of *in situ* soil moisture measurements within a pixel of interest can represent better the spatial pattern of the pixel-wide soil moisture for the purpose of evaluating the downscaling method. Unfortunately, such ground measurements are often not available. The surface condition at CST01 and NST09 sites of Maqu network and Arou site of WATER network is considered homogeneous as described in Section II. *In situ* soil moisture is measured at depth 5 cm at CST01 and NST09 sites and at depth 10 cm at the Arou site. Based on ground measurements from July 2008 to June 2009, soil moisture conditions range from dry ($0.17 \text{ m}^3/\text{m}^3$) in winter to wet ($0.49 \text{ m}^3/\text{m}^3$) at the CST01 site. Soil is relatively dry at site NST09 with a range of soil moisture from 0.05 to 0.27. The range of the soil moisture is from 0.1 to 0.42

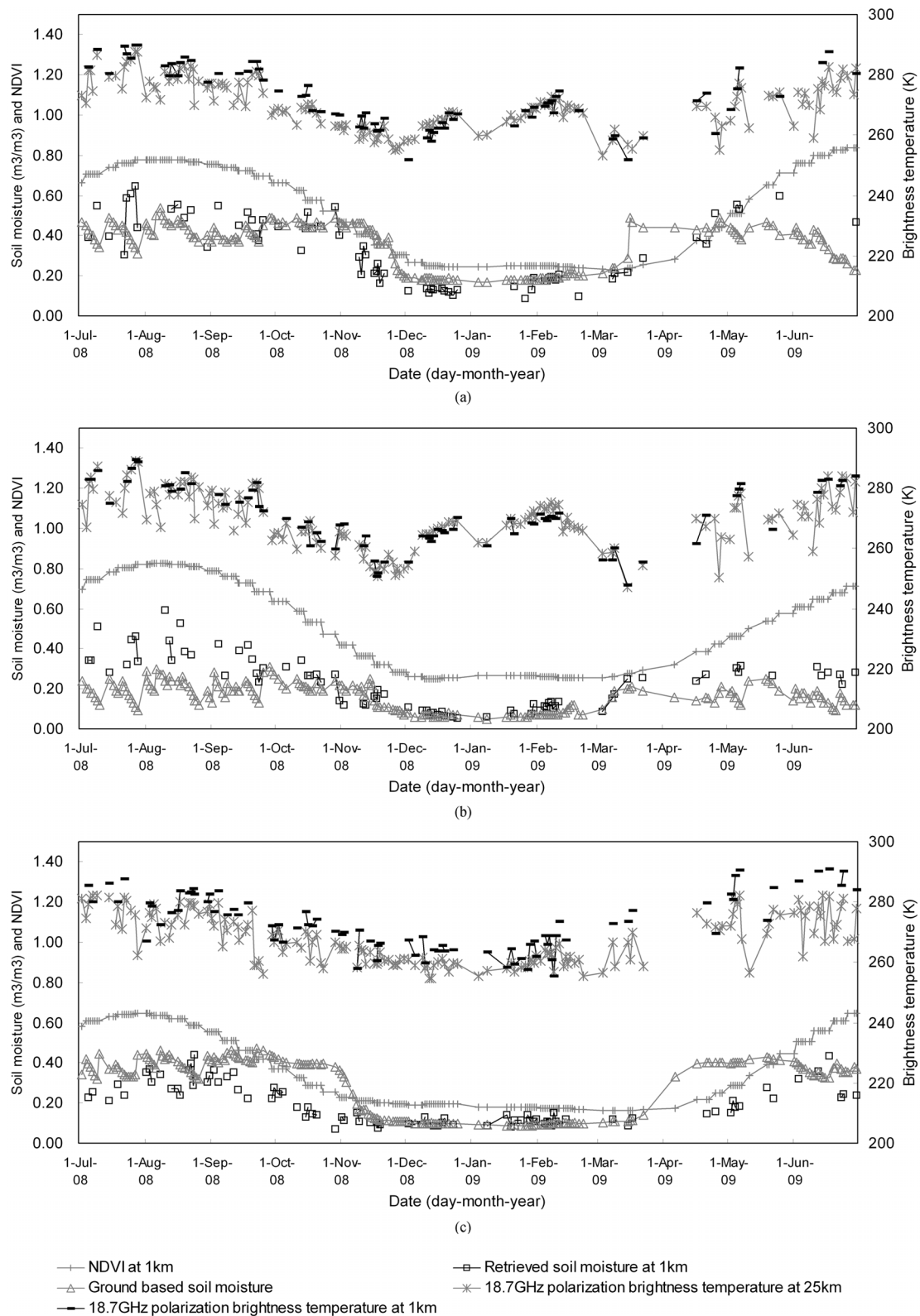


Fig. 7. Time series of retrieved soil moisture, ground measurement and NDVI (on the left y -axis) and 18.7-GHz brightness temperature at 1 km and 25 km in the right y -axis at (a) site CST01, (b) site NST09, and (c) site Arou during the period of July 2008 to June 2009.

at the Arou site. Ground measurements of soil moisture at the three sites, treated as pixel values, are used to compare with the soil moisture values of the retrieved 1-km soil moisture of the pixels surrounding the sites.

Before comparing the retrieved soil moisture with ground measurements, the downscaled 18.7-GHz H-polarization brightness temperature at 1 km is compared with AMSR-E 18.7-GHz H-polarization brightness temperature at 25 km

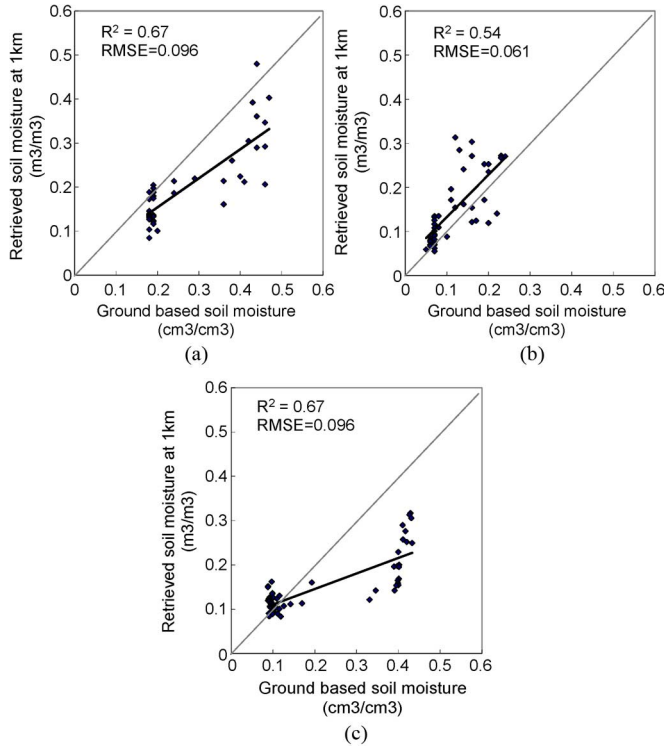


Fig. 8 Comparison of retrieved soil moisture and ground measured soil moisture at site (a) CTS 01, (b) NST09, and (c) Arou for the period from July 2008 to June 2009 under the condition of NDVI lower than 0.5.

at the three sites for the period between July 2008 and June 2009, as shown in Fig. 7. It can be seen that the 18.7-GHz H-polarization brightness temperature at 25 km has similar trends with the ones at 1 km at the three sites. The difference of brightness temperature between 25-km and 1-km resolutions is smaller in winter than in summer. The degraded vegetation in winter time has reduced the spatial variability of soil moisture, which leads to relatively homogeneous spatial distribution of brightness temperature.

The time series of retrieved 1-km soil moisture is compared with *in situ* measurements for the period between July 2008 and June 2009 (Fig. 7). It is observed that the trends of the retrieved soil moisture are similar to the trends of ground measurements in this period, say higher in summer and low in winter at all three sites. However, soil moisture is in general overestimated in most growing season days from July to October 2008 and May to June 2009 at CST01 and NST09 sites [Fig. 7(a), (b)] and underestimated at Arou site [Fig. 7(c)]. In winter season (from November 2008 to March 2009), the retrieved soil moisture is slightly underestimated at the CST01 site [Fig. 7(a)]. Besides the errors on the downscaled brightness temperature at 1 km, one possible reason could be the soil moisture measured at the ground sites cannot represent the soil moisture of a pixel at 1 km; this particularly becomes a problem in growing seasons when land surface wetness is rather inhomogeneous due to snow melting, soil thawing, precipitation, etc. Underestimation at the Arou site is probably attributing to the fact that the depth measured at the Arou site is 10 cm, which is likely wetter than the surface in the growing season, while less difference in winter

time between surface and deeper layers. Further study might be necessary to understand better the discrepancy between the retrieved and measured soil moisture.

Contribution of soil to the sensor at 18.7-GHz frequency is reduced by dense vegetation during growing season. The 18.7-GHz brightness temperature is less sensitive to soil moisture in the area with high vegetation cover; therefore, only the retrieved soil moisture under the condition of NDVI values less than 0.5 is further analyzed in comparison with ground measurements (Fig. 8). The R^2 at the three sites is higher than 0.5, and RMSE is less than 0.12. The smallest value of RMSE is 0.058 at the NST09 site. Among the three sites, the NST09 site is relatively dry with a soil moisture smaller than 0.3, and the variation of soil moisture over time at this site is also small (the range is from 0.04 to 0.3). This implies that the algorithm may work more sufficient under lower soil moisture conditions, which is consistent with the finding in [28] using SSM/I data at the 19.4-GHz frequency. The sensor at 18.7-GHz frequency can observe soil moisture up to the depth of 1–2 cm. The soil moisture observed at 5 cm depth at CST01 site is closer to the retrieved soil moisture than at depth of 10 cm at the Arou site, so the RMSE at CST01 site is lower than that at Arou site with the similar range of soil moisture observed at the two sites.

In general, the trends of the retrieved soil moisture are similar with ground measurements. Errors on the downscaled brightness temperature at 1 km could be one of the reasons that cause the errors on the retrieved soil moisture at the same resolution. When the errors on the downscaled brightness temperature is about 6 K as shown in Section IV-B, errors on the retrieved soil moisture due to the errors on downscaled brightness temperature is about $0.039 \text{ m}^3/\text{m}^3$ with NDVI lower than 0.5. The method is better applicable under relatively drier conditions (soil moisture less than 0.3 in our case) with bare surface or sparsely covered surface by vegetation ($\text{NDVI} < 0.5$).

V. CONCLUSION

This paper proposed a method to retrieve high-resolution soil moisture by downscaling 25-km AMSR-E brightness temperature using high-resolution optical/thermal data. The algorithm for downscaling brightness temperature works under the following conditions: 1) LST is larger than 275 K and 2) the range of NDVI is between 0.1 and 0.5.

The method is applied to the northwest of China. The comparison between the retrieved 1-km soil moisture and the ground measurements at the three experimental sites showed R^2 higher than 0.5 and RMSE less than $0.12 \text{ m}^3/\text{m}^3$. The method works better in drier conditions (soil moisture smaller than $0.3 \text{ m}^3/\text{m}^3$) with bare surface or sparsely covered surface by vegetation ($\text{NDVI} < 0.5$).

The key point of the proposed method is to downscale 25-km AMSR-E 18.7-GHz brightness temperature to 1 km. Compared with the low-frequency band, such as C-band, L-band, the 18.7-GHz band is less sensitive to soil moisture under high vegetation cover, which limits the use of the method. A method of downscaling low-frequency band brightness temperature is therefore necessary to be developed to retrieve high-resolution soil moisture in future study.

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