IOP Conf. Series: Earth and Environmental Science **121** (2018) 052006 doi:10.1088/1755-1315/121/5/052006

Soil moisture retrieval in mining-disturbed areas with temporal high resolution SAR

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Abstract. Using 12 periods RADARSAT-2 HH polarization data and combining with the Alpha approximation model, the soil moisture of the study area was retrieved and then compared with the MODIS retrieval results. Then, the DInSAR results of RADARSAT-2 were used to investigate the effect of high intensity underground mining activities on surface soil moisture. The study found that the soil moisture values of RADARSAT-2 had a good correlation with MODIS retrieval results. In the four comparison groups, the maximum correlation coefficient was 0.599 ($p<0.01$). The comparison among the 72 soil moisture values of the six mining subsidence areas and the non-subsidence areas in the study area in 2012 showed that there were 38 soil moisture values of the non-subsidence area was higher than that of the subsidence area, which indicated that the high-intensity mining activity had a certain negative impact on the surface soil moisture.

1. Introduction

Soil moisture plays an important role in surface and atmospheric transmission and it is an important indicator of water stress, drought monitoring, and agricultural production [1, 2]. The rapid development of remote sensing technology provides effective means for accurate monitoring surface soil moisture in high repetitive coverage and regional scale [3].

The advantages of not restricted by weather conditions and very sensitive to the soil moisture change make the microwave remote sensing more widely used in soil moisture change monitoring. In order to obtain the surface soil moisture, there are two main ways: one is combining the multi-polarization [4, 5], multi-angle [6], multi-frequency [7] or multi-source data (e.g., passive microwave data [8], optical data [9], ground measured data [10]) to separate the contribution of surface roughness and vegetation to the backscattering coefficient, and then further obtain the relationship between soil moisture and backscattering. The other is through the repeated observation of short time interval, using single-polarization, multi-temporal data for surface soil moisture retrieval [11, 12].

Using the temporal RADARSAT-2 HH polarized images and combining the Alpha approximation model proposed by Balenzano [13], the absolute value of surface soil moisture in the arid and semi-arid area along the boundary of Inner Mongolia-Shaanxi provinces was retrieved. Then, the results were compared with the soil moisture values retrieved from MODIS. Finally, according to the DInSAR results of RADARSAT-2, the temporal and spatial variation of surface soil moisture under the complex background of mining area was explored.

2. Study area and data processing

2.1. Study area
The study area (latitude 39°17'N~39°30'N, longitude 109°57'E~110°09'E) is located at the junction of Ejin Horo county in Inner Mongolia and Shenmu county in Shaanxi province, the edge of Mu Us Desert. The annual precipitation in this area is 350~400 mm, and the vegetation coverage is low. Most of the vegetation in the study area are Artemisia and Seepweed. The surface erosion is serious and the ecological environment is very fragile [14].

2.2. RADARSAT-2 data and processing
RADARSAT-2 is a commercial synthetic aperture radar satellite developed by the Canadian Space Agency in cooperation with MDA. The paper chooses RADARSAT-2 single-polarization data that imaging mode is Multilook Fine (MF5,HH) and product level is SLC (slant range product) and the nominal resolution is 8 m (20/01, 13/02, 08/03, 01/04, 25/04, 19/05, 12/06, 06/07, 23/08, 10/10, 27/11 and 21/12/2012).

The paper uses two RADARSAT-2 SLC data (20/01/2012 and 13/02/2012) to extract the subsidence areas. Using the DInSAR workflow tool provided by SARscpae5.2.1©, the surface deformation map is obtained (Figure 1). From Figure 1, several obvious subsidence areas can be seen, and the maximum subsidence value is 0.171 m.

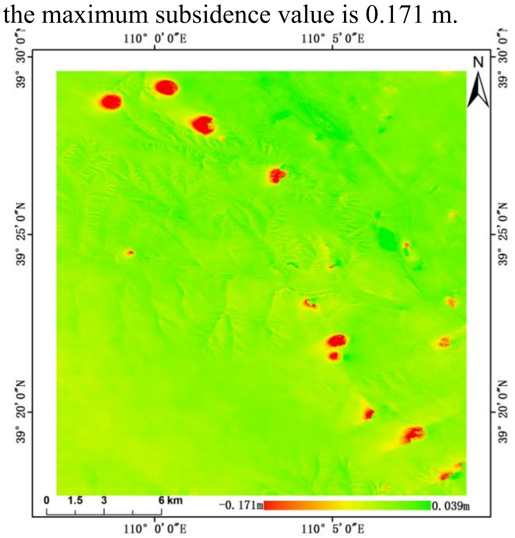

Figure 1. Surface deformation map of the study area.

2.3. MODIS data and processing
The Moderate Resolution Imaging Spectroradiometer (MODIS) product MOD09GA from NASA (https://ladswebnnas/search.html) provides a daily ground reflectivity data of 1 to 7 bands in 500 m resolution. In the paper, the MOD09GA data of 21/01/2012, 26/04/2012, 06/07/2012 and 10/10/2012 were used to retrieve soil moisture in order to analysis the retrieval results of RADARSAT-2.

3. Methodology

3.1. Soil moisture retrieval via RADARSAT-2
For the SAR images acquired with time T1 and T2, the ratio of the backscattering coefficients obtained for these two time can be expressed as a function of soil dielectric constant, radar

incidence angle and polarization mode [13]. The model is called the Alpha approximation model and can be written as:

$$\frac{\sigma_{0,PP}^{T_2}}{\sigma_{0,PP}^{T_1}} \approx \left|\frac{\alpha_{PP}^{T_2}(\theta,\varepsilon_s)}{\alpha_{PP}^{T_1}(\theta,\varepsilon_s)}\right|^2 \tag{1}$$

where PP indicates the polarization mode; T_1 and T_2 indicate the SAR image acquisition time; α_{PP} indicates the polarization amplitude; ε_s indicates the soil dielectric constant.

According to formula (1), the Alpha approximation model can be written as:

$$\left|\alpha_{PP}^{T_2}(\theta,\varepsilon_s)\right| - \left(\frac{\sigma_{0,PP}^{T_2}}{\sigma_{0,PP}^{T_1}}\right)^{1/2} \left|\alpha_{PP}^{T_1}(\theta,\varepsilon_s)\right| = 0 \tag{2}$$

From the equation (2), it can be seen that two observation data can form a linear equation. Therefore, for the N continuous SAR images, we can get M ($M = N-1$) linear equations. By combining the M linear equations, the system of equations can be written as:

$$\begin{bmatrix} 1 & -\left(\frac{\sigma_{0,PP}^{T_1}}{\sigma_{0,PP}^{T_2}}\right)^{1/2} & 0 & \dots & 0 & 0 \\ 0 & 1 & -\left(\frac{\sigma_{0,PP}^{T_2}}{\sigma_{0,PP}^{T_3}}\right)^{1/2} & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & 1 & -\left(\frac{\sigma_{0,PP}^{T_{N-1}}}{\sigma_{0,PP}^{T_N}}\right)^{1/2} \end{bmatrix} \begin{bmatrix} \left|\alpha_{PP}^{1}(\theta,\varepsilon_s)\right| \\ \left|\alpha_{PP}^{2}(\theta,\varepsilon_s)\right| \\ \dots \\ \left|\alpha_{PP}^{N}(\theta,\varepsilon_s)\right| \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \dots \\ 0 \end{bmatrix} \tag{3}$$

The number of equations in the system of equations (3) is less than that of the unknown, so there are countless solutions, and it is an underdetermined question. In order to solve the system of equations, we need to limit the range of α_{PP} to $\alpha_{\min} \le \alpha_{PP}^i \le \alpha_{\max}$ and $1 \le i \le N$. According to the soil characteristics and the incident angle range of the study area, let $\alpha_{\min} = 0.3$ and $\alpha_{\max} = 0.7$.

After obtaining the polarization amplitude value from the system of equations (3), the soil dielectric constant of the study area can be solved by using the small perturbation model. Finally, the soil dielectric constant can be converted into soil moisture values by Dobson soil dielectric mixing model.

3.2. Soil moisture retrieval via MODIS

Yao et al. [15] constructed MODIS shortwave infrared spectral characteristic space by using MODIS 6th and 7th bands and proposed a simple and reliable MODIS shortwave infrared soil moisture index (SIMI). The SIMI formula can be written as:

$$SIMI = |OE| / |OD| = \sqrt{\rho_6^2 + \rho_7^2} / \sqrt{2} \tag{4}$$

where ρ_6 and ρ_7 are the surface reflectance of the 6th and 7th bands, respectively.

Yao et al. [15] used SIMI and the corresponding ground data for regression analysis and gave the soil moisture (M_V) retrieval model. The paper uses the model to retrieve the soil moisture based on SIMI images. And then the soil moisture values are compared with the retrieval results of RADARSAT-2.

4. Results and analysis

4.1. Comparison of soil moisture retrieval results

According to the vegetation cover types, 15 sampling points were selected randomly in every of the surface types. In order to explore the impact of underground high-intensity mining activities on surface soil moisture, 6 typical subsidence areas and corresponding non-subsidence areas were selected for sampling and comparison (Figure 2).

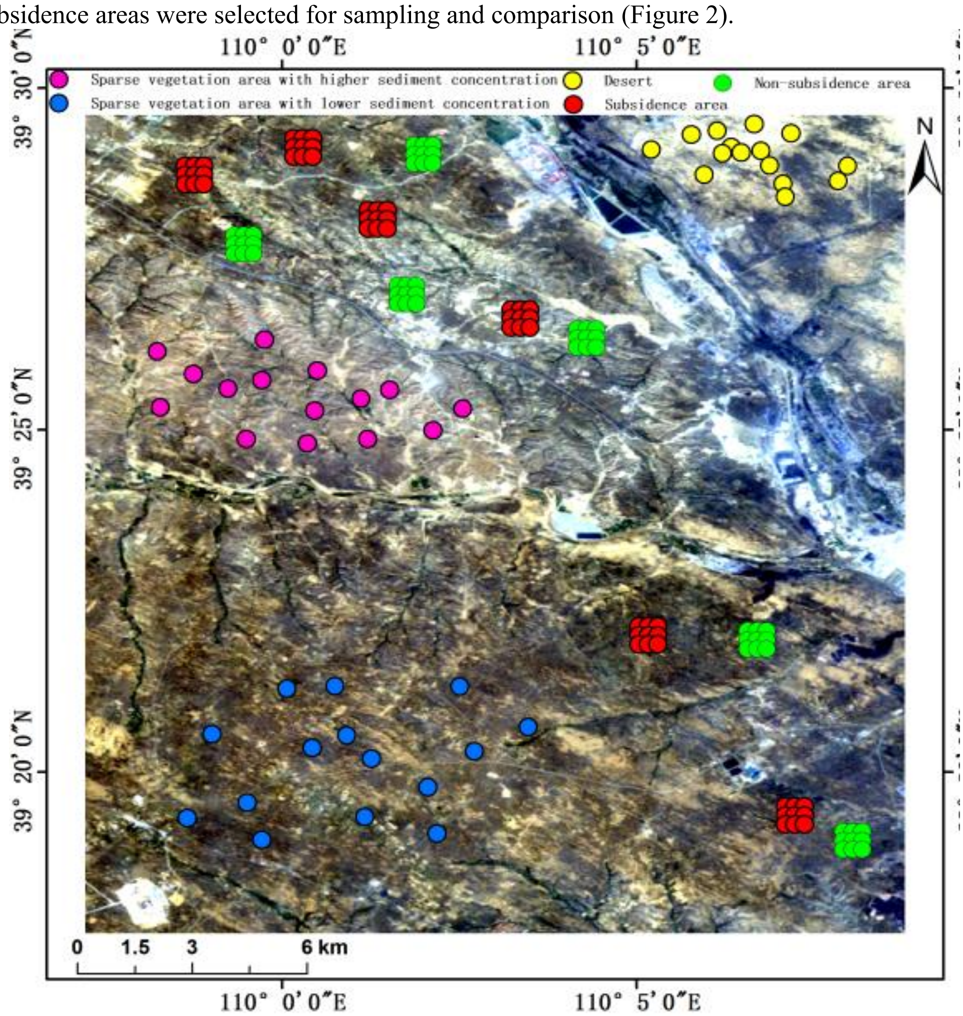

Figure 2. Distribution map of sampling points.

According to the sample values, the soil moisture retrieval results of the two methods are shown in Figure 3:

It can be seen from the Figure 3, the proportion of the sampling points which the absolute error is within 3% in the four comparison groups is 33.3%, 55.6%, 17.8% and 22.2%. The absolute error of all sampling points is less than 10%. The maximum correlation coefficient is 0.599 and reaches a significant level ($P<0.01$) through the statistical test. All of the results indicate the reliability of the RADARSAT-2 retrieval model. From the Figure 3, however, we can see that the RADARSAT-2 retrieval results are more volatile. The main reason for this phenomenon is considered inconsistent resolution of the two types of data.

4.2. Soil moisture in subsidence area and non-subsidence area

72 average values can be obtained in 6 subsidence areas or non-subsidence areas in the whole study area. Then compare the average values in subsidence area with non-subsidence area, as is shown in Figure 4:

Comparing each of the soil moisture value in subsidence area and non-subsidence area, the statistics shows that there are 38 soil moisture values of the non-subsidence area is higher than that of the subsidence area. So the effect of subsidence on surface soil moisture is not obvious, which is consistent with the result monitored by Bian et al [16] using remote sensing data.

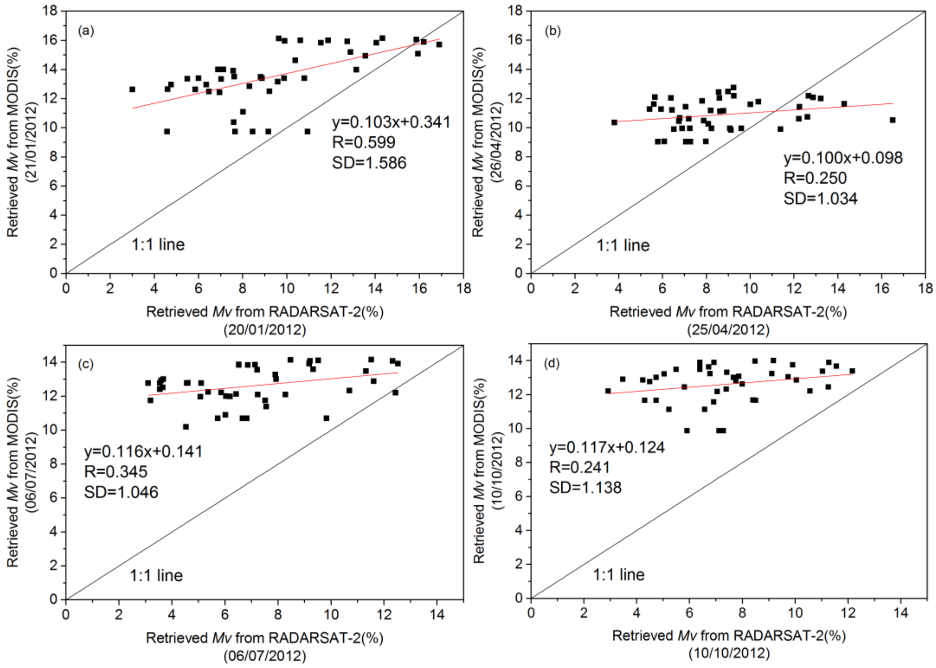

Figure 3. Comparison of soil moisture retrieved from RADARSAT-2 and MODIS.

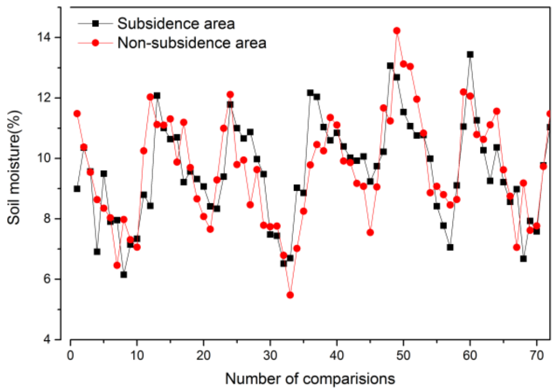

Figure 4. Comparison of soil moisture in subsidence area and non-subsidence area.

5. Conclusions

The main conclusions are as follows:

(1) The results of statistical analysis showed that the two inversion methods had a good consistency with each other. In the four comparison groups, the highest proportion of sampling points which the absolute error was within 3% were 55.6% and the absolute error of all sampling points was less than 10%. The maximum correlation coefficient was 0.599 ($p<0.01$). All of the above results indicate the applicability of the Alpha approximation model in the study area.

(2) The soil moisture values retrieved from RADARSAT-2 were used to analyze the impact of subsidence on surface soil moisture. The statistical result showed that there were 38 soil moisture values of the non-subsidence area was higher than that of the subsidence area in 2012, accounting for 53% of the total, which indicated that the high-intensity mining activity

had a certain negative impact on the surface soil moisture, but the impact was not yet significant.

Acknowledgment
This research is jointly supported by the project of the National Natural Science Foundation of China and Shenhua Coal Industry Group Co., Ltd. (Grant No. U1261106 and U1261206).

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